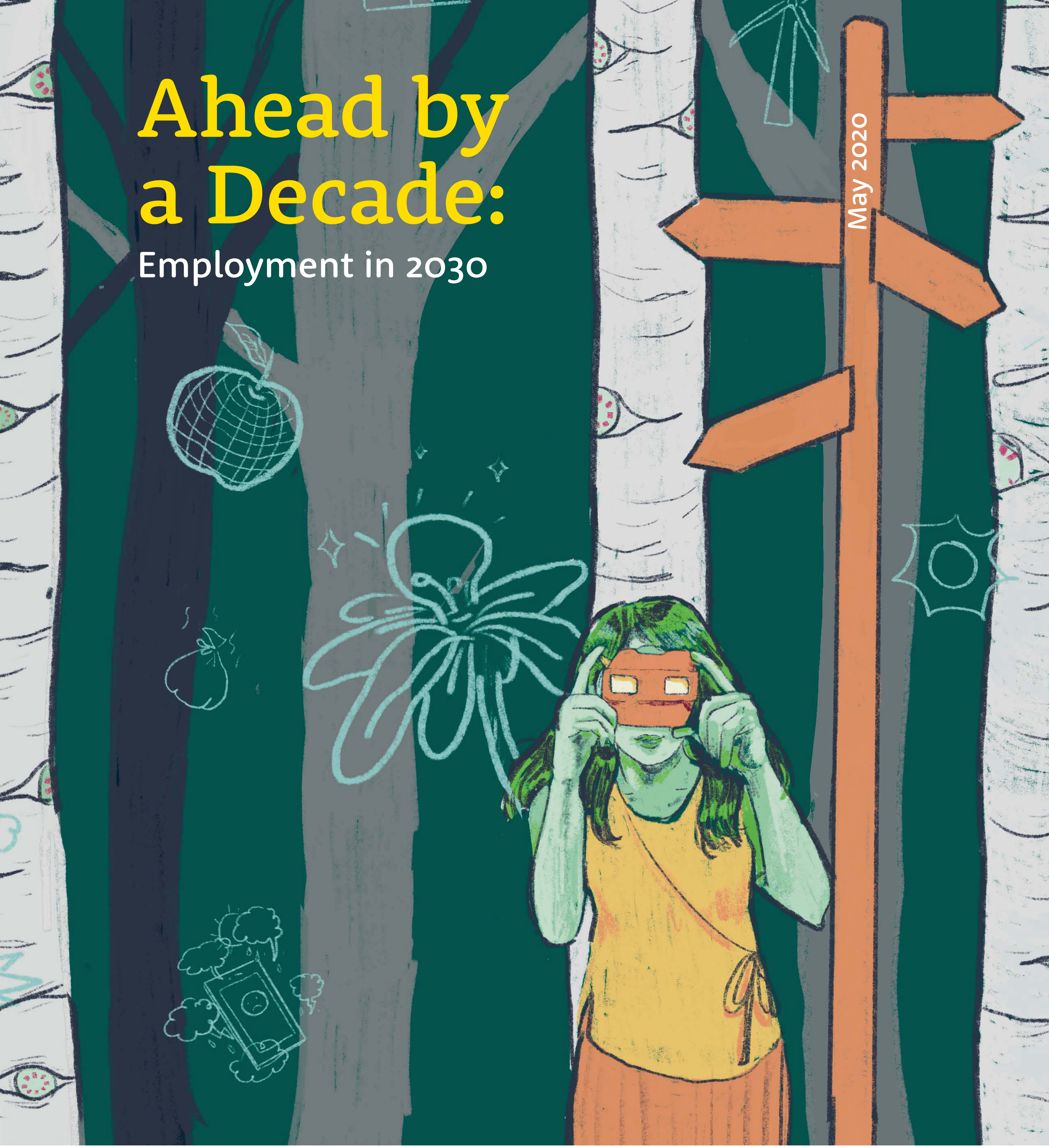
Ahead by a Decade:

Employment in 2030

May 2020



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ACKNOWLEDGEMENTS + SPECIAL THANKS

The Brookfield Institute's research is supported by internal and external advisors and partners who provide subject matter expertise and linkages to both policymaker and practitioner perspectives. For their contributions and insight into this report, we would like to thank:

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With special thanks to graphic designer Lindsay Smail and illustrator Jesseca Buizon.

The Brookfield Institute for Innovation + Entrepreneurship (BII+E) is an independent and nonpartisan policy institute, housed within Ryerson University, that is dedicated to building a prosperous Canada where everyone has the opportunity to thrive in an inclusive, resilient economy. BII+E generates forward-looking insights and stimulates new thinking to advance actionable innovation policy in Canada.

ISBN: 978-1-77417-018-2

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Thank you to the 121 experts who generously gave their time to participate at one of six full day workshops. While their identities will remain anonymous, the Employment in 2030 initiative would not be possible without the data they contributed.

CONVENING PARTNERS

PARTNERS + FUNDERS

This report was funded in part by the Government of Canada's Sectoral Initiative Program and the Max Bell Foundation. The opinions and interpretations in this publication are those of the authors and do not necessarily reflect those of the Government of Canada or the Max Bell Foundation.

This project was carried out in partnership with Nesta, an innovation foundation based in the United Kingdom (UK) that has previously piloted this research methodology in the UK and the United States, in collaboration with Pearson and Oxford Martin School.

This project was made possible with support from Element AI. Element AI is an artificial intelligence solutions provider that gives organisations unparalleled access to cutting-edge technology.

A NOTE RE: FORECASTS IN TIMES OF EXTREME UNCERTAINTY

Although this report is being released in the first half of 2020, the vast majority of the work putting together the Forecast of Canadian Occupational Growth (FCOG) occurred in 2018 and 2019.

This is not unusual for large scale projects of this nature: there are almost always inevitable lags between finishing raw research and releasing a polished, understandable, externally-reviewed version for public consumption. However, in this case, the emergence of the COVID-19 crisis and its enormously disruptive effect on the world present a particular challenge: Are the results of an occupational growth forecast created before the crisis still relevant?

We believe the answer is a strong "yes." The findings of the report and, more generally, the FCOG provide a very helpful guide for thinking about long-term employment and skills trends in Canada between now and 2030.

The global pandemic and accompanying economic crisis will undoubtedly have an impact on these trends. Some trends may accelerate, new ones will emerge, others may slow down or stop. Future versions of this forecast will necessarily incorporate the impact of the crisis on long-term employment trends.

But, many of these trends are deeply rooted in economic, social, political, technological, and environmental changes that we believe will continue. And the time frame of the forecast—targeting 2030, not 2021—is designed to focus on the long-term.

Forecasts, at their best, are snapshots of the future from a particular point in time. They are almost never 100% right; no one ever predicts the future with certainty. Rather, the best forecasts are meant to be tools to help guide our thinking about the future—an exercise that is inherently clouded with uncertainty.

Similarly, the FCOG is not an attempt to paint a definitive picture of the future of Canadian employment. It is a complementary tool which, used alongside other sources of future-looking information, can guide the design of skills development policies and programs that are more likely to be resilient into the future.

As Canada and the world grapple with how to recover from the current COVID-19 crisis, thinking about the long-term will be more important than ever. The need to design policy and program supports that will be effective into the future is more urgent as we seek to support workers and businesses not only in weathering this crisis, but in emerging as strong or stronger than before.

We hope this forecast may be a useful contribution to this challenge.

Sincerely,

Sean Mullin
Executive Director
Brookfield Institute for Innovation + Entrepreneurship

NAVIGATING A DECADE AHEAD

This report explores the final forecast and results of the *Employment in 2030* initiative. The reading times below suggest specific sections depending on areas of interest and time available:

15 MINUTES:

30 MINUTES:

1 HOUR:

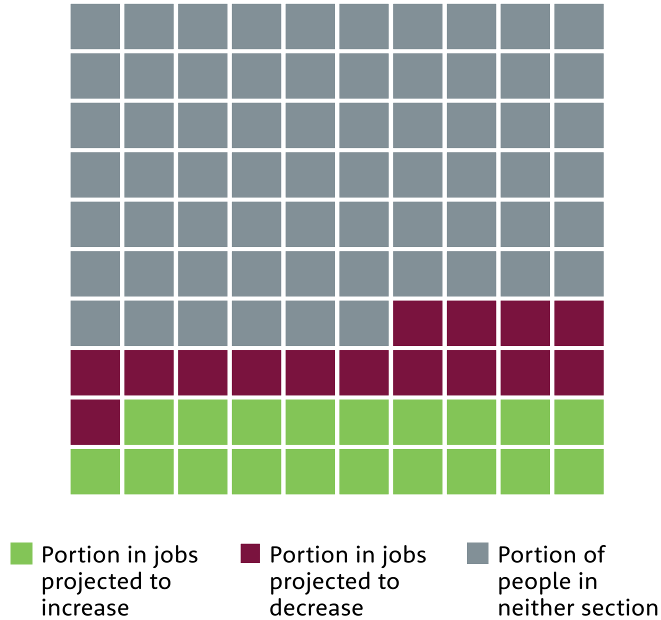
TABLE OF CONTENTS

EXECUTIVE SUMMARY

Preparing for the future of work is one of the biggest challenges facing policymakers, employers, educators, service providers, and unions. The Brookfield Institute's Forecast of Canadian Occupational Growth provides a new tool for understanding how Canada's labour market could evolve over the next decade, shaped by potentially disruptive drivers ranging from technological change to resource scarcity and an aging population. Ahead by a Decade: Employment in 2030 highlights key insights from this forecast, exploring how Canadian occupations may grow or decline relative to national employment over the next ten years. The interdisciplinary methodology behind this analysis involves foresight research, expert insights, and machine learning. This novel approach was used to create projections informed by each occupation's skill, ability, and knowledge requirements, and by data gathered through six cross-country workshops.

This report highlights:

+ **The jobs projected to grow or decline:**
A third of Canada's workers are currently in occupations projected to change in the next decade: 19% of Canadian workers are in occupations projected to grow; 15% are in occupations projected to decline in employment share (the portion of all Canadian workers they employ). Occupations in health, natural, and applied sciences are projected to grow, along with those with a high degree of service orientation and technical expertise. Occupations in manufacturing and utilities, however, are generally projected to decline by 2030. Both workers and employers will need support in navigating these potential shifts.



+ **Skills and abilities expected to be important across the labour market:**
Five social skills and cognitive abilities emerge as foundational for the workforce of the future: fluency of ideas, memorization, instructing, persuasion, and service orientation. Echoing recent research, these traits encompass a worker's capability to brainstorm, to absorb new information of different kinds, to teach, to influence opinions and behaviour, and to identify ways to help people. They are likely to become increasingly necessary for workers to remain resilient as the labour market evolves in the next decade. In addition, this report highlights a number of other areas that can enhance a worker's resilience when paired with existing education and experience.

- **The needs and realities of different workers:** Risks, resilience, and opportunities are unevenly distributed across Canada's people and regions. Key examples include:

  – Men are more likely than women to work in occupations projected to grow—and in occupations projected to decline. This suggests that the future of work for women may present less opportunity as well as less risk.

  – Workers in occupations projected to decline earn less than those in occupations projected to increase or remain stable, which may make it harder to navigate job disruption. Notably, while fewer women are working in occupations projected to decline, those who are may be more vulnerable to change: they are paid significantly less than men in these occupations ($33,552 versus $42,883).

  – First-generation immigrants are more likely to work in occupations projected to grow when compared to the workforce average. This is a positive indicator, as immigration is expected to remain a main driver of workforce growth in Canada.

  – While some visible minority workers are, on average, more likely to hold jobs in occupations projected to grow, certain groups may face more risk. Notably, over one fifth of men who identify as Filipino, Southeast Asian, Black, or Latin American, as well as those who do not identify as part of a visible minority, are in occupations projected to shrink.

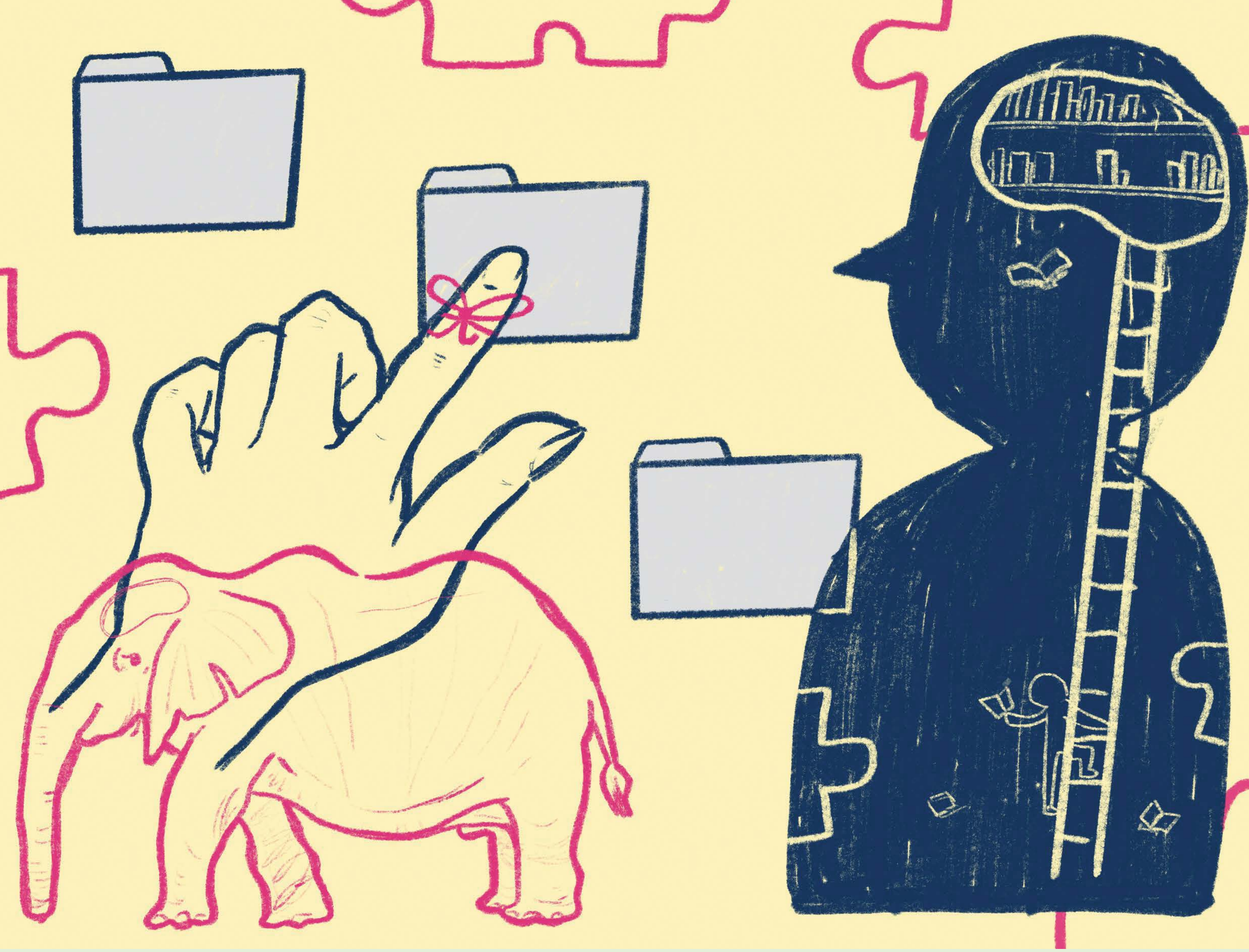
  – Available data suggests that among all workers, Indigenous peoples are some of the most likely to be employed in occupations projected to decline in employment share. However, there is a large gap in labour market information available for Indigenous peoples, making these insights less certain. This underlines the need for investments in Indigenous-led initiatives to better enable Indigenous communities and workers to respond to labour market change.

  – There is no single province or territory that is better positioned to navigate future employment change; however workers in Nunavut and Saskatchewan are slightly less likely to work in occupations projected to grow and more likely to work in declining ones.

  – Almost half of workers in growing occupations have a bachelor's degree or higher, compared to only 13% of those in occupations projected to decline in importance. This suggests that higher education will become increasingly necessary to access high-potential jobs over the next decade.

- **Recommendations for helping workers and employers navigate change:**
  Skill development and employment policies and initiatives should be designed not only to respond to immediate needs, but with future resilience in mind. This forecast points to opportunities for policy and program design to proactively support worker and employer resilience by highlighting the occupations, industries, regions, and people who may face more disruption, as well as the skills and abilities that could help them adjust.

The forecast and this accompanying report provide a picture of the future that is complementary to existing research and forecasts, but is not a definitive prediction. It introduces a new perspective on the future of employment that differs from the Canadian Occupational Projection System (COPS), which largely relies on extrapolation from past trends. *Ahead by a Decade* is designed to help policymakers, program designers, educators, and service providers identify and respond to potential risks and opportunities, better positioning workers and employers to navigate a dynamic labour market.



INTRODUCTION

Preparing Canadians for the future of work is one of the biggest challenges facing policymakers, employers, educators, service providers, and unions. While the future is necessarily undefined, there are signals now of what might come—indications of how the labour market may evolve. Currently, however, Canada lacks a clear picture of how different skills and occupations could grow or decline in prominence as a result of complex forces spanning, for example, technological, environmental, and demographic change. It also lacks future-focused analyses of how these trends might impact different geographies, industries, and people.

To help address this challenge, the Brookfield Institute for Innovation + Entrepreneurship (BII+E) has developed an occupational and skills forecast for the year 2030, working alongside Nesta, a leading global innovation foundation, partners across Canada, and a multi-sector advisory committee. This forecast is driven by a scan of mature and emerging trends impacting Canada's labour market, by expert perspectives on how these trends might influence demand for different occupations, and by a machine learning model that extrapolates expert opinions to all occupations based on the skills, abilities, and areas of knowledge they require. This mixed-methods approach is designed to complement existing forecasting methods, such as that of the Canadian Occupational Projection System (COPS), which tend to rely on extrapolation from past trends and may underestimate the potential for disruption. It also looks beyond occupations, to examine the skills that are likely to be important across the labour market in the coming decade.

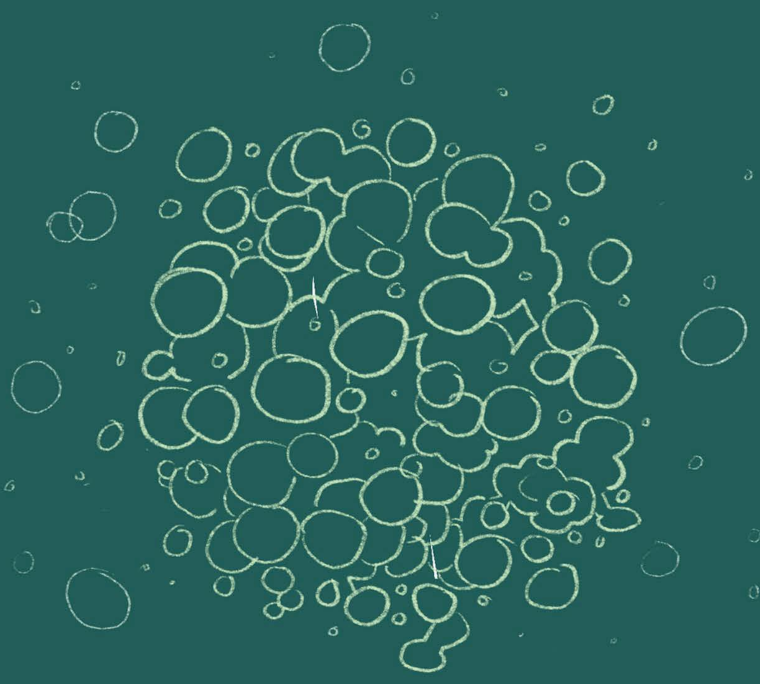
The *Employment in 2030* project is based on an approach pioneered by Nesta in the United Kingdom and the United States as part of their *Future of Skills* project. The Brookfield Institute extends Nesta's approach, with adjustments to account for the unique characteristics of Canada's workforce, and modifies aspects of it based on the lessons learned from the original application. This research was made possible through the support of the Government of Canada's Sectoral Initiative Program and the Max Bell Foundation.

This report describes the results of BII+E's forecast. It highlights the occupations, skills, and abilities that are projected to experience and drive change. It also explores who is currently employed in occupations expected to experience growth or decline, and who has the skills and abilities identified as foundational, with the aim of drawing attention to groups that may be more or less vulnerable to change. Finally, this report offers a detailed explanation of the methodology behind the forecast. This report is not intended to present a definitive picture of what will happen. Rather it offers a practical and nuanced picture of possible changes in order to inform the design of training and employment policies, programs, and tools aimed at improving the resilience of workers and employers in Canada.

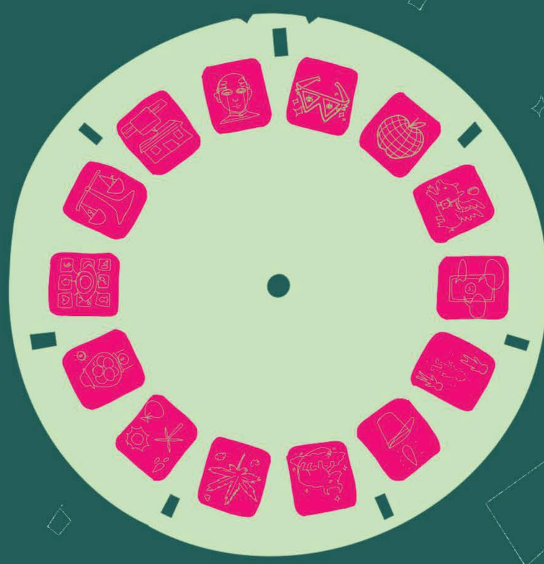
GOALS

1. Provide a skills forecast to Canadian educators, policymakers, workers, and firms with granular, actionable information on demand for skills and occupations in 10 to 15 years.
2. Outline the risks and opportunities faced by Canadian workers and firms across skill sets, geographies, ages, incomes, and other demographic characteristics.
3. Inform the design of education, training, and economic development policies and programs, as well as modern social safety nets.

PHASE 1



Gather 600+ Signals of Change in the Canadian labour market



Identify 31 Trends

Turn and Face the Strange: Changes impacting the future of Employment explores the dynamics of 31 related trends and their possible implications for Canada and its labour market in the year of 2030 and beyond.

PHASE 2

Host 6 expert workshops across Canada

Sign of the Times: Expert insights about employment in 2030 delves into how experts forecast select jobs may change in the future, and which trends may be driving the transitions.

PHASE 3

Create a skills and employment forecast driven by a machine-learning prediction model and expert insights

The Forecast of Canadian Occupational Growth (FCOG), and its accompanying report, *Ahead by a Decade: Employment in 2030,* provide a new perspective on how Canada's employment landscape could evolve in the future—and how these changes could impact different people. It also includes an interactive web app and publicly-available forecast data.

CONTEXT

Already familiar with the future of work landscape? Look ahead to Methodology *on page 11*

COMPLEX FORCES ARE DRIVING LABOUR MARKET CHANGE

Change in the Canadian labour market is evident, necessary, and driven by multiple, interacting forces.[1] [2] There is a broad range of demographic, economic, technological, and geopolitical trends which not only have profound implications for labour markets, but create challenges for policy in their own right.[3] Globalization, urbanization, growing inequality, and environmental sustainability are only some of the trends that have changed the nature of work.[4] [5] [6] [7]

For example, the automation of tasks, ranging from scheduling to manufacturing, has the potential to continue to impact most jobs.[8] [9] However, jobs with different task compositions, held by people of different ages, genders, and in different industries or firm structures, are changing in diverse ways.[10] [11] [12] These interactions make the future of job and skill demand difficult to predict but important to prepare for, especially since they do not impact all workers or occupations equally. As a result, policy responses are needed now to increase resilience across Canada's workforce.

The first report released as part of the *Employment in 2030* project, *Turn and Face the Strange*, explores some of these trends and their potential impacts for the Canadian labour force in the next decade.[13]

THE SKILLS AND OCCUPATIONS LANDSCAPE IS CHANGING

As these trends impact which jobs are growing or declining, they also impact the nature of the jobs and the skills required to perform them. Specific occupations and the general labour market are experiencing a systemic shift toward non-routine tasks.[14 15 16 17] When the tasks associated with occupations change, the demand for skills also shifts. In addition, urbanization is increasing labour market concentration, causing skill requirements to increase.[18] While companies do seek to reduce costs and offshore certain tasks, they tend to maintain those that call for interpersonal skills.[19] As new technologies become more accessible and effective at making predictions, the value and demand for human judgment and creativity may dramatically increase.[20 21 22]

Recent studies suggest that the largest increase in demand involves cognitive and social skills that are complementary to more specific and sometimes technical competencies.[23 24 25] Since 1980, occupations requiring these soft skills have not only grown as a share of the labour force in the US, but also in terms of wages.[26] These results have implications for educational choices and policy. Rather than pitting digital or technical skills against social or creative ones, they highlight the importance of a broad, interdisciplinary education as workers with diverse skills tend to be more resilient.[27 28 29] While policymakers and educators are increasingly expanding the goals of education systems around these 21st century skills, the question of which skills to focus on and how to best teach and integrate them into formal assessment frameworks remains.[30]

New occupations are also emerging, from frontier jobs that create and manage emerging technology, to work designed to provide services to those with very high levels of wealth.[31 32 33] However, these jobs may be out of reach for many, and questions have been raised about the potential for an overall decline in the well-paying, middle-skill, non-degree jobs that have been traditional paths to career advancement into the middle class.[34]

THE LABOUR MARKET DATA IS LIMITED BUT EVOLVING

The labour market information available to help explain current labour market dynamics and inform projections about potential future change is imperfect but evolving. Workers, employers, and policymakers have more information than ever but not all of it is actionable. New granular sources of information such as skills data scraped from online job advertisements are available alongside macro indicators such as employment, vacancies, and income. This allows for experimentation with different methods for researching the evolution and future of work.[35 36 37]

Skills + occupations

Occupations are often used as the main unit of study through which to assess current and potential future dynamics in labour market demand. However, there is growing interest in understanding changes in the underlying tasks or worker characteristics—such as skills—that comprise these occupations. These approaches have different benefits and shortcomings.[38] Considering impacts at an occupational rather than task level can miss considerable variation in the tasks involved in an occupation and, by extension, in the skills and abilities required to fulfill these tasks.[39] However, governmental occupational classifications have widely available data that reflects the overall national economy, even if this information is updated slowly. In turn, there is a growing range of possible sources of skills data, from government sources such as the US Bureau of Labour Statistics and Employment and Social Development Canada (ESDC), to private databases that draw from online job advertisements. The most stable and comparable way to track skills, however, remains occupational composition. This analysis uses the more granular information available at the skill level, while also framing its results around Canadian occupations.

Emerging + merging methodologies

Governments, international institutions, and researchers are making further efforts to complement existing research methods, find new sources, and look toward the future of work. For example, the Canadian government is using strategic foresight methodologies to explore trends, disruptions, and potential future scenarios to assess what the future may look like.[40 41 42]

Many employment forecasts draw on indicators of volume (employment growth, unemployment rate, vacancy rates), price (wage growth), work intensity (growth in hours worked, incidence of overtime), and quality (incidence of under-qualification and training), but these are likely to yield vague insights in isolation.[43] Others have focused on skills information drawn from employer surveys. While this method has been one of the most popular across G20 countries, and provides valuable insight into employer demand, employer skill assessments can be subjective and inconsistent.[44 45 46] Other approaches are starting to focus on the long term, analyzing indicators of occupational and skills change in specific industry or geographic contexts, drawing on qualitative and quantitative insights.[47 48] The BII+E's forecast draws on a unique combination of foresight, expert insights, and quantitative modelling to complement existing approaches.

GAPS IN LABOUR MARKET INFORMATION CALL FOR NEW APPROACHES

Change in Canada's labour market is multifaceted, driven by a range of forces that are likely to have uneven impacts across different people, geographies, jobs, and sectors. At the same time, available labour market data and existing forecasts provide a limited picture of what the future might hold. This suggests that a mixed-method approach that combines forward-looking trends analysis, expert human judgement and quantitative modelling, drawing on occupational and skills data, is a useful way to explore the possibilities of the future of work.

Up-to-date on the project's research methods? Jump ahead to A Forecast of Employment and Skills in 2030 *on page 29.*

The creation of the *Employment in 2030* occupational forecast involved a variety of research methods. However, it centers around expert opinion and the underlying skills, abilities, and knowledge traits that are required of workers in any given occupation. *Employment in 2030* had three major phases: conducting and sharing of trends research, design and execution of expert workshops, and the creation and analysis of an occupational forecast for 2030. The data gathered through workshops, informed by labour market trends, matched with the skills makeup of an occupation, and processed by BII+E's machine-learning prediction model created a set of occupational projections for almost all Canadian professions. The resulting forecast provides a picture of how employment in different jobs could change across Canada's economy in the future. It allows for the identification of the fundamental skills, knowledge areas, and abilities that may drive employment changes in the next 10 years.

This mixed qualitative and quantitative approach is informed by the work of Nesta and the University of Oxford in *The Future of Skills: Employment in 2030*, where they created projections for the US and the UK. However, in order to adapt this research to the Canadian context, certain aspects of the methodology were modified in important ways including the trend research approach, the data collection method, and the classification algorithm.

The approach presented below aims to complement more conventional quantitative forecasts, such as the Canadian Occupational Projection System (COPS). Traditional forecasts rely heavily on employment data and economic models, extrapolating from past trends. They are limited in their ability to identify new drivers of change or structural breaks, which may mean that previous assumptions break down or become invalid. Social, technological, and environmental trends are more difficult to take into account.

While expert opinion is also fallible, the projections described in this report offer a valuable window into how experts with direct experience in various areas of the labour market expect it might change in the next decade, how impactful trends might interact, and how they might depart from the past. Together, these different forecasting approaches can help inform policy decisions by describing and preparing for different possible futures.

PHASE 1: TRENDS RESEARCH

The goal of this stage was to identify broad trends with the potential to impact the Canadian labour market in 10-15 years. While experts were invited to participate in this study based on their respective areas of expertise, the intent of the trends research was to encourage participants to consider less common ideas about the future of work.

Research on the trends impacting the Canadian labour market involved horizon scanning, which identifies signals of change by drawing from academic journals, popular media, and fringe sources.[49] BII+E identified a wide range of signals of change that had the potential to affect the workforce, from a variety of sources such as academic journals, popular media, and fringe news sources. Surveying over 600 sources, the scanning process identified 31 meso trends, with varying levels of maturity: mature, emerging, and weak signals.

In turn, these reflected aspects of seven wider megatrends, identified in Nesta's earlier research: technological change, globalization, demographic change, environmental sustainability, urbanization, increasing inequality, and political uncertainty.[50] This research took place in the fall of 2018, and is described in the first *Employment in 2030 report,* Turn and Face the Strange: Changes Impacting the Future of Employment in Canada.[51]

Box 1: Trend maturity

+ **Mature trends:** Trends that are well known, are backed by robust evidence, and are highly likely to impact the future in some way.

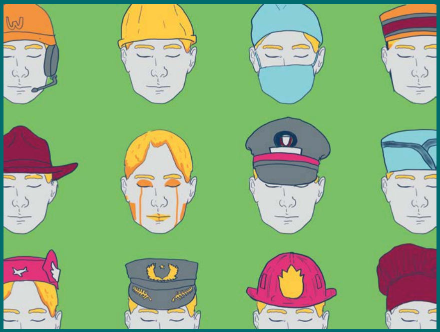
+ **Emerging trends:** Trends of which there is some awareness, with some evidence of impact. They are less developed and potentially newer, but likely to shape the direction the future takes.

+ **Weak signal trends:** Trends that may or may not impact the future, but have the potential to do so in a significant way. They are much less developed than either emerging or mature trends, and how they might evolve is unclear.

31 Trends

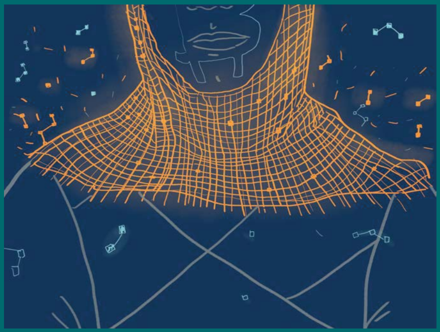
from Turn and Face the Strange*, a BII+E report released in March, 2019*

TECHNOLOGICAL CHANGE



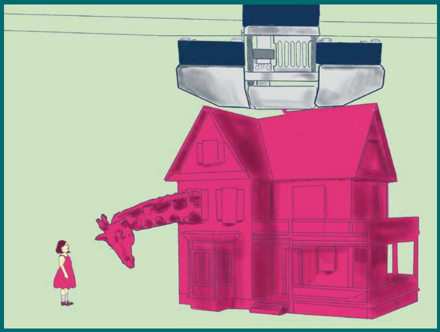
AI EVERYTHING: AI may impact and potentially disrupt every industry.

VR + AR EXPERIENCES: Virtual and Augmented Reality may transform the way Canadians engage with a range of experiences, from training to gaming.



BLOCKCHAIN: Blockchain adoption may change the security and authenticity of important transactions including banking, land rights, high value goods, insurance and voting.

DIGITAL DETOX: Finding the cost of digital connectedness too high, Canadians are making deliberate decisions to unplug from technology to achieve a healthier life balance.



3D PRINTING: 3D printing is gearing up to change the way we produce and consume goods in the future.

WE ARE FAMGA: Facebook, Amazon, Microsoft, Google, Apple (FAMGA) are redefining the technology industry and dominating multiple markets, leaving limited space for others.

DIGITAL IDENTITY: Information about us and our families is being used to create digital identities.

HUMANS, AUGMENTED: Brain enhancements may elevate human capabilities.

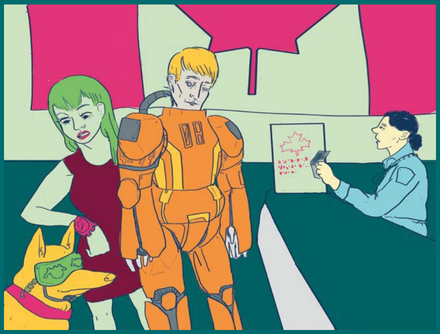
TECHNOLOGICAL CHANGE *continued*

TECHNOLOGICAL FEAR: The pervasiveness of our digital connections is leading to deep fear and anxiety about technology.

RIGHTS OF AI: AI may transition from being understood as software to being considered beings, therefore achieving a new status and basic rights.

CREATIVE AI: Creative AI has the potential to automate creative tasks typically deemed automation-resilient.

GLOBALIZATION



TECH TALENT IMMIGRATION: Canada is using creative mechanisms to address tech talent shortages.

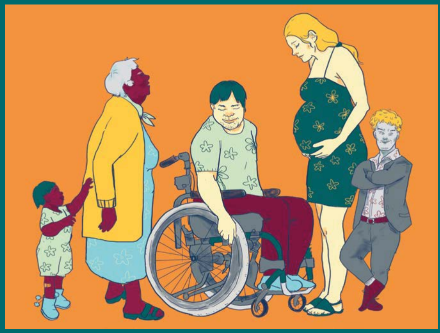
DEMOGRAPHIC CHANGE

WORKING RETIREMENT: Seniors may meld work and retirement well into their eighties and nineties.

CONNECTED BUT LONELY: Mental illness may become even more widespread, alongside increased technological connections.

LIFELONG LEARNING: Learning never stops.

WORK + LIFE INTEGRATION: Our personal and professional lives are melding, erasing the distinction between work and leisure hours.



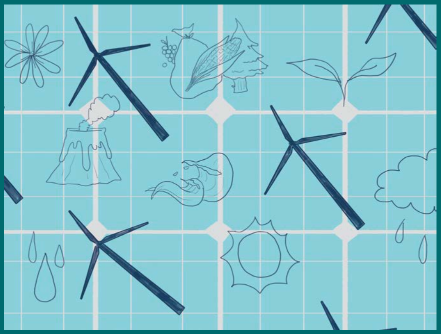
MAINSTREAM INCLUSIVE DESIGN: Understanding that one size does not fit all, inclusive design may create a new market of opportunities.

ENVIRONMENTAL SUSTAINABILITY

RESOURCE SCARCITY: Clean air, water, sand may all become scarce and extremely valuable resources.

WILDFIRES, FLOODING + MUDSLIDES: Climate change may increase the instances of wildfires, floods and mudslides in Canada.

CLIMATE REFUGEES: Canada may see an influx of refugees due to major climate change disruptions in the rest of the world.



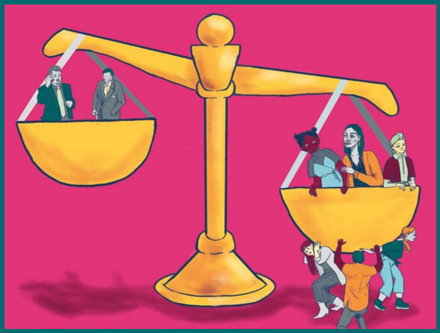
ALTERNATIVE ENERGY: Experimental and sustainable energy sources could provide abundant, affordable energy for all.

URBANIZATION

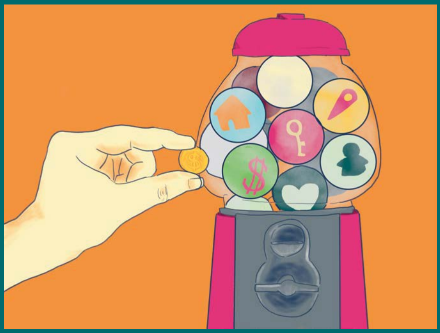
SUBURBAN BOOM: Canada's suburban areas are growing faster than the overall population.

INCREASING INEQUALITY

DISAPPEARING MIDDLE CLASS: The middle class may be disappearing and overstretched by debt, increasing the polarization between rich and poor.



REBALANCING GENDER EQUALITY: The rebalancing of gender equality could disrupt private and public institutions.



PERSONAL DATA OWNERSHIP: Concerns over personal data may create new ownership and revenue models.

INEQUALITY continued

DECLINE OF CAPITALISM: Millennials may push for a new economic system to replace capitalism.

POLITICAL UNCERTAINTY

INTERNATIONAL TENSIONS: New sources of international tensions may drive investment in security, including security applications of AI.

OTHER

ENTREPRENEURIAL SPIRIT: Entrepreneurship-related work and the entrepreneurial spirit may become the dominant career path with many Canadians creating their own opportunities rather than committing to a single employer.

MANDATORY CREATIVITY: Creativity could become critical for all Canadians, not just for the arts and design community.

EDUCATION REIMAGINED: Work is changing, driving demand for learning how to learn instead of memorizing information, paving the way for new models of education for K-12 learners.

CANNABIS ECONOMY: Canada becomes second nation in the world to legalize marijuana, creating immense new market opportunities.

PHASE 2: WORKSHOPS

To gather expert opinion data, BII+E hosted six interactive workshops across Canada in collaboration with five regional partners in order to capture Canada's regional and economic diversity. At each location, participants explored trends impacting the labour market as identified in *Turn and Face the Strange*, analyzed potential scenarios, and forecasted potential changes for select occupations. The data collected consists of the responses of 121 participants with expertise in labour market trends, where they signaled how employment in select occupations may change by the year 2030.

Hosts

+ Canada West Foundation, Calgary
+ Brookfield Institute at Ryerson University, Toronto
+ Cold Climate Innovation at Yukon College, Whitehorse
+ SFU Public Square, Vancouver
+ Percolab, Montreal
+ Newfoundland and Labrador Workforce Innovation Centre (NLWIC) at CNA, St. John's

Goal + considerations

The primary goal of the workshops was to collect high-quality survey responses on how expert participants believe employment may change over the next decade. This data then informed a machine-learning prediction model.

In order to achieve this, human-centred design principles guided the workshop design:

+ A profile clearly defined the target participants of the sessions.
+ To account for potential disparities in participant backgrounds, all activities began by providing context-setting information that allowed everyone to fully participate. As each expert had different levels of exposure to the topics explored during the workshop, from foresight exercises to knowledge of particular occupations, this proved extremely valuable.
+ The final agenda was the result of careful iteration, testing, and prototyping, given the need for consistency in the survey delivery.

Box 2: Participant profile

The participant profile developed for workshop attendees included experts who:

+ had an understanding of broad (vs. occupation-specific) labour market information and trends,
+ were from diverse demographic and geographic backgrounds,
+ were employed in a range of sectors, in mid- to senior-level management,
+ were comfortable with making decisions under conditions of uncertainty and ambiguity,
+ were open to participating in new research methods, and
+ were able to attend a full day workshop.

Workshop inputs

Using the 31 trends from *Turn and Face the Strange* as framing, these workshops entailed a series of future-focused activities designed specifically for *Employment in 2030*. At each location, participants explored the trends research, discussed how these trends may impact jobs in the future, and considered what new jobs may emerge. During the main activity, experts rated how they expected employment to change in the next 10–15 years at occupation stations. Data provided for each occupation included:

+ A description of the occupational group to be considered, as defined by the National Occupational Classification (NOC), and examples of the job titles it comprises, as defined by Employment and Social Development Canada.[52]

+ The top five sectors of employment for the occupation and the corresponding portion of workers employed in each, from the 2016 Census.

+ The most important skills, abilities, and knowledge attributes for workers in the occupation according to the US Occupational Information Network (O*NET) database.

+ The historical and projected number of workers in an occupation, and share of national employment held by that occupation, based on Census data from 2001-2011, and the Canadian Occupational Projections System (COPS) 2016.[53]

For more details on the workshop design, see How to Design a Workshop for the Future of Employment and the workshop insights report, Signs of the Times: Expert Insights about Employment in 2030.[54] [55]

PHASE 3: EMPLOYMENT IN 2030 FORECAST

Prediction model

Model inputs

The model used to extrapolate expert projections had two major sets of inputs. First, a set of 485 Canadian occupations and their associated skills, ability, and knowledge traits enables this study to identify potential occupational changes based on worker attributes.[56] Second, the data collected from expert workshops trained the model and made projections across national occupations possible.

*Skills, abilities, knowledge importance scores from O*NET*

The skills data driving this forecast comes from the O*NET database; a US-based labour market information repository. It contains standardised descriptors of US occupations which are publicly accessible and continuously updated.[57] O*NET data is common in skills and labour literature examining the attributes of workers and jobs.[58] To create skill-driven projections and insights, this analysis uses O*NET categories from the worker-oriented portion of the taxonomy: abilities, knowledge, and skills. These three categories, containing 120 variables, are more effective at delving deeper into worker traits that are often amalgamated into a *skills* label.[59]

In order to adapt this data for the Canadian context, BII+E developed a crosswalk that links US O*NET occupations to their Canadian counterparts. This matched Canadian occupational codes to their respective descriptor scores. The crosswalk and the accompanying methodology are available in Connecting the Dots: Linking Canadian Occupations to Skills Data.[60]

Box 3: O*NET skills, knowledge, and abilities data

Abilities are enduring attributes that influence how a worker approaches tasks and how they acquire work-relevant knowledge and skills. Skills are developed procedures and capacities to work with given knowledge. Knowledge, in turn, denotes a set of principles and facts that applies in a general domain.[61] Together, these allow for more granular analysis and segmentation of the attributes that may drive Canadian employment growth.

Abilities: Enduring attributes of the individual that influence performance.

+ e.g. Oral Comprehension, Deductive Reasoning, Visualization.

Skills: Developed capacities that facilitate learning, the more rapid acquisition of knowledge, and the performance of activities that occur across jobs.

+ e.g. Critical Thinking, Active Listening, Quality Control Analysis.

Knowledge: Organised sets of principles and facts applying in general domains.

+ e.g. Sales and Marketing, Chemistry, English Language.

For each trait in the above categories, O*NET provides a score that measures how important any given trait is for each occupation. O*NET also includes scores for level, or the "degree to which a particular descriptor is required or needed to perform the occupation." However, as in The Future of Skills, this forecast only considers an occupation's importance score for the skills, knowledge areas, and abilities it may require.[62] More details on this methodological choice can be found in Appendix A: O*NET skills, knowledge, and abilities data.

*Source: O*NET Content Model*[63]

Expert survey data

Through the workshops, 121 experts submitted survey responses, forecasting whether 45 select Canadian occupations would increase, decrease, or remain constant in share of employment by the year 2030.[64] Fifteen of these occupations were benchmarks and common across regions, while the remaining 30 were region-specific. Participants at each session rated five regional occupations, which were selected based on local employment and importance. The final dataset consisted of 2,420 responses.

In order to unpack experts' ratings and better understand what might be driving them, the ratings were compared to historical trends and to other forecasts, as well as to one another across regions. See Appendix A: Expert Survey Data for more details.

Rated Occupations

With 500 national occupations, experts could only examine how a select number of occupations may change in the next 10-15 years.[65] It was critical to choose occupations that would provide the model with information on the widest range of worker traits possible to reduce its uncertainty. As a result, the occupation selection method aimed to create a small, fully representative, and non-overlapping subset of occupations. During Phase 2, participants were asked to rate the 15 benchmark and 5 rotating regional occupations detailed in Tables 1 and 2.

Benchmark occupations

At all workshops, participants rated the same 15 benchmark occupations. This set was chosen by prioritizing occupations that would be the most informative for the model.[66] They also allowed for the comparison of workshop data across regions.

Table 1: **Benchmark occupations**

Code	Occupation
0013	Senior managers—financial, communications, and other business services
0111	Financial managers
1416	Court clerks
2141	Industrial and manufacturing engineers
2223	Forestry technologists and technicians
2281	Computer network technicians
3234	Paramedical occupations
4215	Instructors of persons with disabilities
6722	Operators and attendants in amusement, recreation, and sport
7333	Electrical mechanics
8231	Underground production and development miners
9212	Supervisors, petroleum, gas and chemical processing, and utilities
9422	Plastics processing machine operators
9532	Furniture and fixture assemblers and inspectors
9617	Labourers in food, beverage, and associated products processing

Regional occupations

At each workshop, experts submitted survey responses for five occupations that were regionally important. There were two main goals guiding the selection of these occupations: 1) to have direct expert ratings for regionally and nationally important occupations, and 2) to harness expertise on regionally-concentrated occupations. Hence, this set of occupations contains those that were most important in terms of employment levels, occupational concentration, and relative regional dependence, according to regional data from the 2016 Census.[67] This importance ranking was measured through an aggregate score described in Appendix A: Occupation Selection.

More information on the occupation selection process is available in the BII+E blog [Farmers, Clerks, and Engineers: A Look at How We Selected the Occupations Informing Our Forecast of Employment in 2030].

Table 2: **Regional occupations**

Code	Occupation
Alberta, Manitoba, Saskatchewan	
0821	Managers in agriculture
8431	General farm workers
7312	Heavy-duty equipment mechanics
9232	Central control and process operators, petroleum, gas, and chemical processing
8232	Oil and gas well drillers, servicers, testers, and related workers
Ontario	
6232	Real estate agents and salespersons
4165	Health policy researchers, consultants, and program officers
0631	Restaurant and food service managers
6221	Technical sales specialists—wholesale trade
4112	Lawyers and Quebec notaries
Territories	
2271	Air pilots, flight engineers, and flying instructors
4422	Correctional service officers
6523	Airline ticket and service agents
7534	Air transport ramp attendants
7271	Carpenters
British Columbia	
6321	Chefs
1311	Accounting technicians and bookkeepers
5241	Graphic designers and illustrators
7294	Painters and decorators (except interior decorators)
0632	Accommodation service managers
Quebec	
7514	Delivery and courier service drivers
6731	Light duty cleaners
1521	Shippers and receivers
6322	Cooks
6622	Store shelf stockers, clerks, and order fillers
Atlantic	
8262	Fishermen/women
9463	Fish and seafood plant workers
3012	Registered nurses and registered psychiatric nurses
7252	Steamfitters, pipefitters, and sprinkler system installers
3234	Paramedical occupations

Learning problem

BII+E designed a model that generates probability estimates of how workshop participants may have rated occupations they had not seen during the workshops. It aims to provide an expert-driven and data-based picture of the skills, abilities, knowledge traits, and occupations that may be important and growing by 2030.

This study uses expert answers to the following question: "In 2030, this occupation's share of total employment in Canada will: (increase/remain constant/decrease)."[68] While participants also submitted responses to whether the number of workers in an occupation would change, these estimates would offer limited information about employment growth relative to other occupations.[69] As a result, all the findings presented in this report refer to changes to the share of an occupation as a percentage of total employment and not to the number of people employed.

BII+E's model learned from this expert data based on each of the benchmark and regional occupation's importance scores. Then, based on underlying patterns found in the skill, knowledge, and ability composition of occupations, it extrapolated and generated predictions on the remaining Canadian NOC codes.

The model

The principal predictive model for this study was a random forest algorithm. A range of modelling approaches were considered, including Gaussian processes, other Bayesian approaches, and support vector machines. However, based on the structure and nature of the data collected, the learning problem, model performance, and advice from technical advisors, a random forest model was selected. More information on this process is available in Appendix B: Model selection.

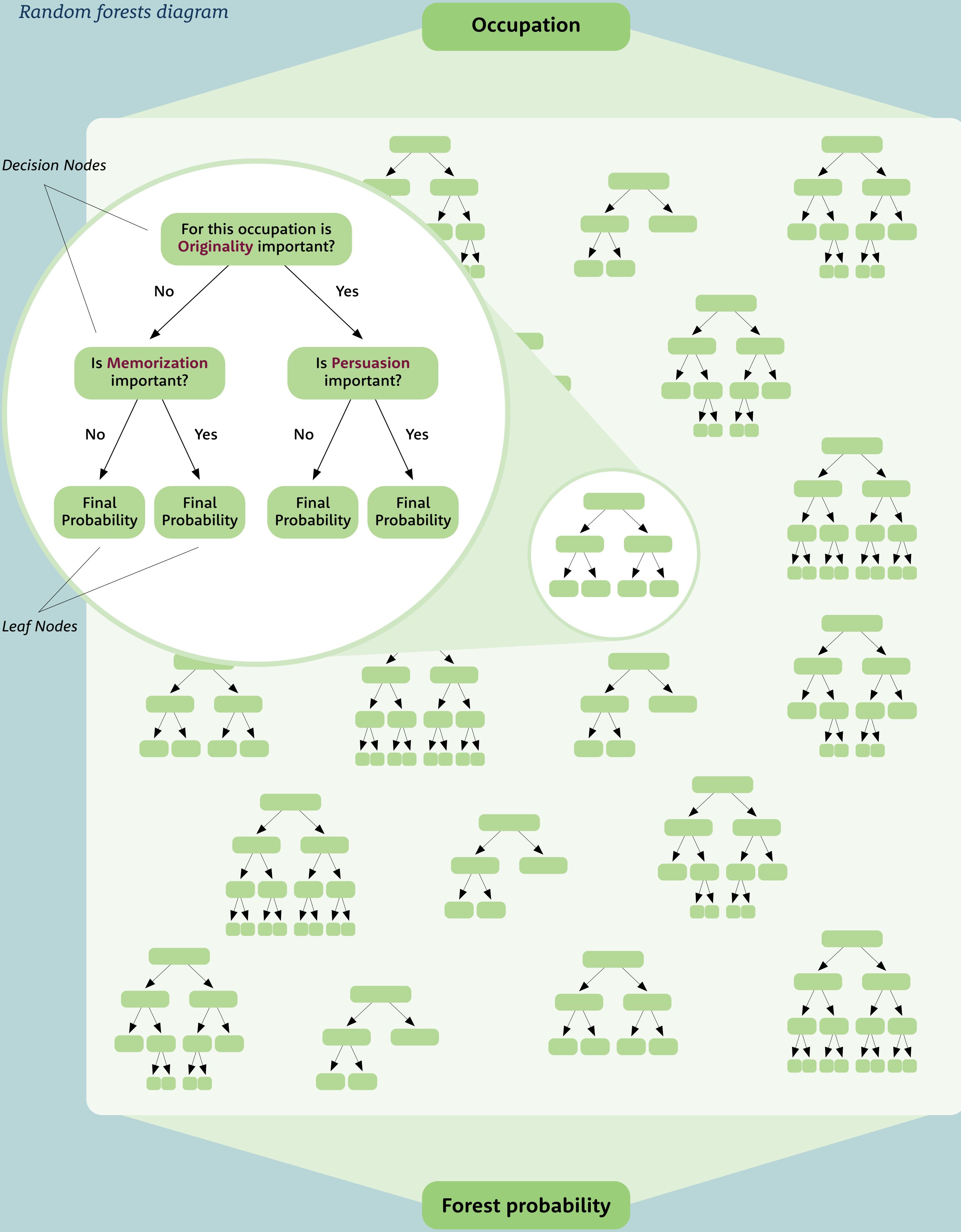
Box 4: Random forests at a glance

Random forest models are an extension of a simple and widely used tool: the decision tree.[70] A decision tree consists of a series of questions (usually binary), called **decision nodes** that end in final choices called **leaf nodes**. A decision tree in machine learning is an automation of that process for the purpose of classification or regression. In this case, the question asked at each node concerns the score of a particular skill (e.g. does this occupation have an importance score higher or lower than a certain value in the skill *originality*?).

Overfitting happens when an algorithm corresponds too closely or exactly to the data available and fails to generalise. When a model overfits to the data, it captures the noise and treats it as an underlying model structure. While decision trees are good classifiers, if one allows a tree to get big enough it can perfectly summarize any data set. This becomes a hindrance when the model processes new data.

Random forests mitigate this risk. They are a collection of decision trees, where each tree is trained on a random *subset* of observations and a random *subset* of variables. Each tree only gets access to a portion of the information available. The forests then comprise many decision trees that are *decorrelated*, making their average less prone to overfitting. It is important to note that since this process is random, each run of the algorithm will yield slightly different results. Certain extensions expand the classification use of random forests, and yield probability estimates instead of final choices in each leaf node.[71] This is the approach used for this forecast.

Random forests diagram



Random forest classifier + probability estimator
For each benchmark and regional occupations, expert input and the associated skill, ability, and knowledge scores trained BII+E's random forest probability estimation model. This extension of a standard random forest creates trees with predicted probability leaf nodes instead of classification ones. It achieves this by running the training set through the fully built and trained model, analyzing the selected O*NET features, and calculating the portion of observations that are 'true' in the final node. In this case, this would be the number of occupations in the final nodes that were projected to grow by experts.

Preparing the training set
During the workshop, experts submitted one of three ternary values—increase, remain constant, or decrease. However, all explored models performed better at predicting participant's answers when they were binned. Binned answers were coded as either *increase* or *not increase*, where the latter includes both *constant* and *decrease*. In general, the model experienced challenges in identifying occupations that received a *constant* label, and generated more accurate results when it only considered the binary options of *increase* or *not increase*. After these adjustments, the model's output is the estimated probability that an expert would have classified an occupation as experiencing *increase*, given its associated skill, ability, and knowledge scores.

Feature selection
The goal of feature selection is to improve model performance by identifying variables that make the model predictions more accurate, while filtering out noisy traits. Random forests are sensitive to the number of variables selected to make each tree. For instance, too low a number can cause a tree to overfit while a higher number increases correlations between trees.

Feature selection reduces this risk of overfitting (see Box 3). The algorithm used in this case was *Sequential Forward Floating Selection* (SFFS). It runs the random forest model through feature combinations, adding and removing variables until it selects a set that achieves the highest prediction accuracy.[72] As a result, the final predictive model considers a small subset of traits rather than all the skill, knowledge, and ability scores available. More details on the use of SFFS and the variables chosen through this process can be found in Appendix B: Feature Selection.

Testing + generating projections
The random forest model processed the expert data using k-fold cross-validations to reduce the possibility of overfitting (see Appendix B: Testing method). The resulting predictions were then compared to the true portion of experts who rated the sample occupations as *increase*. The primary method of evaluating these predicted values was to calculate the absolute difference, or *mean absolute error* (MAE) between the estimates and the true observed values. Additionally, confusion matrices and a comparison of the overall distribution of the estimates and expert ratings provide complementary information about the accuracy of the model results. Appendix C: Model analysis provides more details regarding model performance.

The decrease model
The binned model focuses on the probability of experts deeming an occupation as increasing or not increasing in employment share. In such a model, a low probability of increase cannot be interpreted as a high predicted probability of decrease, since it may be that most experts ranked it as constant. So, while it signals where the opportunities may lie, it does not provide a clear picture of the type of occupations and skills that experts identify as at likely to decline in share given their skill, ability, and knowledge composition.

To address this challenge, a converse model that predicts the probability of decrease was created. The labels were binned in a corresponding way, where *increase* and *constant* responses are labeled *not decrease* category, while *decrease* remains its own class. Apart from the encoded categories, the process was the same and created a separate set of predictions.

Results
Once the model is trained and tuned on the 45 occupations covered by the survey data, the remaining 440 occupations are inputted along

with their skill, ability, and knowledge scores. **The models then produce two projections:**

+ **The probability that experts would classify the occupation as increasing in employment share (the *increase* or growth projection).**

+ **The probability that experts would classify the occupation as decreasing in employment share (or the *decrease* or decline projection)**

For the purposes of this analysis, an occupation is projected to grow or decline in employment share when the corresponding model estimate is greater than 0.5.

Comparing results: The Gaussian process model

As a point of comparison, this forecast also provides a set of scores created using a Gaussian process approach. This is a similar model to the one presented in Nesta's The Future of Skills: Employment in 2030.[73] While this model performed slightly worse when asked to predict original survey responses, its estimates provide a comparison point and robustness check to the main forecast presented here. More details are available in Appendix C: Gaussian Process comparison.

Identifying skills for 2030

A key component of the project was to find the skills, knowledge traits, and abilities that would be most useful and transferable for a worker in 2030, given the expert forecast. The approach outlined below identifies the traits that **frequently** and **consistently** increased the probability of growth, according to expert data.

These criteria may be fulfilled by a trait **independently** or **conditionally**. They are **independently** met when a high importance score in a skill, ability, or knowledge area always improves the probability of increase regardless of the scores of any other features. Alternatively, an attribute may **conditionally** increase the probability of growth in employment share for an occupation. This occurs when a skill, knowledge, or ability only provides a positive influence when paired with another trait above a particular importance score. These criteria guide the identification of **foundational**, **complementary**, and **augmenting** traits in this report.

Box 5: Foundational, complementary, and augmenting traits

Foundational traits: Traits that consistently, frequently, and independently improve an occupation's growth projection. Given the strict criteria set out, only 5 traits arise as foundational: Fluency of ideas, memorization, service orientation, instruction, and persuasion.

Complementary traits: Traits that complement key skills, abilities, or knowledge already important for workers in a given broad occupational category, such as managerial or health occupations. As a result, they make the occupation more likely to be classified as growing by the model. *Key traits* are those important to all occupations in a broad category.

Augmenting traits: Traits that, when already important, augment the positive influence of a given knowledge area, such as Psychology or Mathematics. They are important to identify in order to help trainers and educators equip their students with skills and abilities that will build their resilience in a changing labour market.

A model-based approach

One of the primary advantages of the random forest model is the accessibility of the mechanics through which the model reaches a conclusion. A random forest tracks how an individual occupation moves through decision points and exactly how the occupation's importance scores contribute to the final prediction. To take advantage of these aspects of the model, this analysis targets the individual paths of each tree in the model to find the skills, abilities, and knowledge areas that may become most relevant in 2030.

Making a full-feature model
Feature selection was key to improving the model's performance. However, only considering the traits chosen by the SFFS algorithm would provide a very limited picture of the worker attributes that may become important in 2030. SFFS would not limit its selection to traits that drive a high probability of increase, only those that best identify whether experts would classify an occupation as increasing in employment share or not. In fact, even if there were many skills, abilities, or knowledge areas that did so, the selection algorithm would want to pick the smallest number of them.

As a result, BII+E ran an expanded version of the random forest model, which includes all 120 skills, abilities, and knowledge features in order to highlight the ones that may drive employment in the next decade. While this skills analysis model is less accurate, it has both greater explanatory power and comparable outputs. Both models therefore inform the insights summarized in this report.

Identifying useful skills: a structural approach
The primary approach aims to identify the worker traits that, when important in an occupation, consistently increase its projected probability of growing in employment share and appear frequently across occupations.

As described in Box 4, a random forest is a collection of decision trees, which are a set of decision paths from a root node to leaf nodes that give a final probability score. In each tree, an occupation travels along a path and, at every node, an O*NET skill, ability, or knowledge score is compared against a threshold. If the score is greater than the threshold, then a feature is relatively important and the occupation *goes right*, otherwise it *goes left*. This process continues at every node until the occupation reaches a leaf node and is assigned final probability prediction. The decision threshold at each node is calculated by the model to split the data in a way that yields the most accurate classification.

At every decision node and for every tree, the model records the probability prediction at that point in the process. As a result, the influence of a feature at a node is also the difference in probability of increase before and after the decision was made. The influence is positive if, at the threshold, a higher score (*going right*) caused the probability to grow or a lower score (*going left*) caused it to fall. The influence is negative if, at the threshold, a higher score (*going right*) caused the probability to fall or a lower score (*going left*) caused it to rise. The Decision Tree Diagram illustrates this progression. The purpose of the structural approach is to answer the following question: as decisions are made based on skill, knowledge, or ability scores, when and for which traits does it help to have a high value?

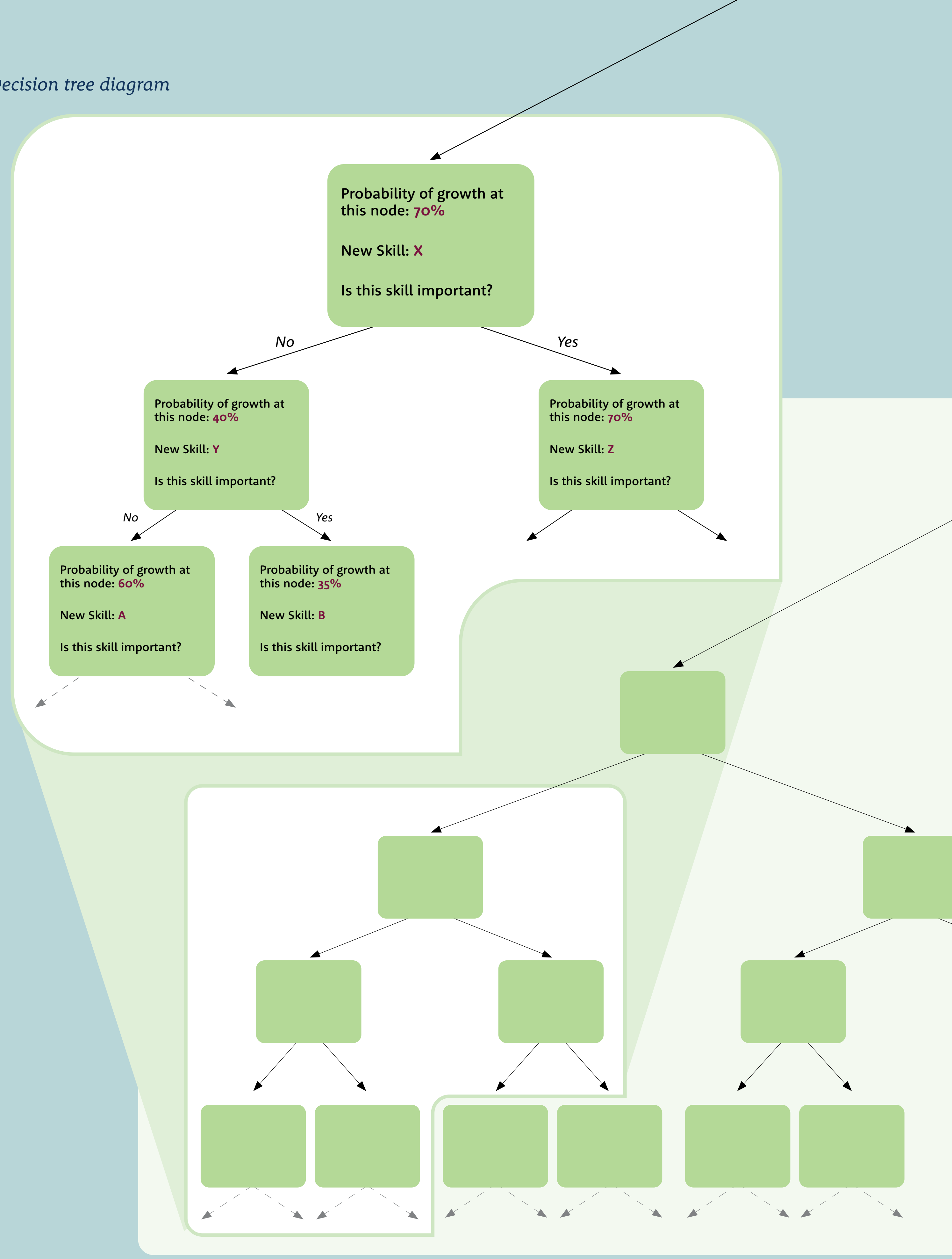
Skills for 2030

Foundational skills: Independently important worker attributes
Foundational traits are those that have a positive influence on an occupation's probability of growth at nearly all of the decision nodes where they are present. As such, they fulfill the consistency and frequency criteria. In order to identify the most independently important among all skills, abilities, and knowledge areas, BII+E analyzed all decision nodes in the random forest. The traits with the highest portion of positive influence (at least 95%) over ten runs of the full model emerged as this report's foundational skills and abilities.[74] This process ensures that the random aspect of the model does not unduly influence the results.

This analysis also considers the influence of a foundational trait on an entire path, or the series of decisions from root to leaf node. This step provides more information on the contextual effect of a particular skill, ability, or knowledge area. For each foundational trait, the results section discusses whether it significantly changes the final probability of increase for an occupation when compared to the average probability of increase across the predictive model.

Complementary and augmenting skills: Conditionally valuable worker attributes
Complementary traits are those that, when paired with another trait, frequently and consistently

Decision tree diagram



contribute to an occupation's probability of increased employment share over time. This portion of the analysis examines pairings rather than single attributes. Paths and decision nodes are only considered if they include decision nodes for the specified skill pairings, in a given order and direction. For example, this analysis may consider how often Computers and Electronics knowledge contributes positively to the probability that experts would assess an occupation's employment share as likely to increase, when the occupation also had a high importance score in Deductive Reasoning earlier in its path. The results section of this report focuses on two types of pairings. It presents those that may be relevant for broad occupational groups, as well as those that may help workers harness a particular field of knowledge in the 2030 workforce.

Complementary traits: Occupation-specific pairings

While some traits, such as those identified as foundational, may be important across the Canadian labour market in the next decade, others may be more relevant to certain occupations. The process to find these consists of two steps. First, the main three key attributes of each broad occupational group are identified. In this case, key attributes are the skills, abilities, and knowledge traits that are important to all occupations within that group. Second, similar to the criteria used for foundational skills, this process selects the complementary traits that have a positive influence on the occupation's probability of growth at least 95% of the times they co-occur.

Augmenting traits: Knowledge-specific pairings

The second type of pairing identifies the skills and abilities that make each knowledge trait have a consistent positive influence. In other words, it pinpoints the circumstances under which a given field of knowledge or education can be most useful. Augmenting traits, if important in any occupation, would make their corresponding knowledge traits have a positive impact in 95% of cases.

Limitations

Data

Existing LMI

+ The O*NET taxonomy:
  – The taxonomy is maintained through US surveys on US occupations. This study assumes that the worker requirements are similar in Canada when some differences are undoubtedly present. However, lacking a similar resource in Canada, O*NET is often used.[75]
  – O*NET's surveys are resource intensive, and only a portion of occupations are included in the survey each iteration. As a result, the database is slow to update and includes the responses of relatively few experts.
+ Alternative skill taxonomies:
  – Skill classifications alternative to O*NET are available such as: the European Skills, Competences, Qualifications, and Occupations (ESCO); the Essential Skills defined by Employment and Social Development Canada (ESDC); and private taxonomies such as the one created by Burning Glass Technologies. However, the need for a complete structure that is granular and equally available for all Canadian regions made O*NET the most appropriate. [76]
+ Occupational classification:
  – The National Occupational Classification (NOC) is slow to change and update.
  – Within each occupational code, there are a broad range of job titles that can be fairly distinct in practice. However, they

  - are generalised to require the same set of skill, ability, and knowledge traits.
  - The forecast necessarily relies on classifications of current occupations. It therefore may not take into account entirely new occupations that do not fit within the current classifications but may emerge in future.
+ The Canadian Census of Population:
  - The Census captures limited and incomplete data on Indigenous Peoples. Indigenous groups are increasingly participating in the collection of Census responses, but in the 2016 Census there were 14 reserves and settlements that were incompletely enumerated. While this was partly due to natural disasters, it is also affected by the complex history of the misuse of data collected from Indigenous peoples. [77] [78]

Expert survey

+ Participants were overwhelmingly based in the workshop's host city. While they are exposed to wider LMI knowledge through their work, hosting more workshops across different regions may have encouraged participants from other areas to participate.

Model

+ The model predicts expert answers based on the skills, abilities, and knowledge attributes required for the job. It does not take in any data on industrial trends or shocks, other than what might be encoded in the survey ratings. If two different occupations have the same skill requirements, then the model would treat them as equal regardless of the actual job descriptions or industrial contexts. This exclusion may cause the model to perform worse in generating predictions for occupations whose changes in employment are driven by factors other than underlying skills. An example of these may be the occupations that presented the highest error when comparing model predictions to expert ratings, listed in Appendix C.
+ The model predicts the portion of experts who would have given a certain answer. While in testing the error rate is quite low, there is still an error rate. As a result, it is important to interpret the estimates with caution. Comparing probability ranges is significantly more reliable than the exact number generated by the model.

Skills and demographic analysis

+ The analysis assumes that the skills, knowledge, and abilities a person has are the same as the ones required by the occupation in which they are currently employed. Workers, however, may possess traits that are not identified by the occupations in which they are currently employed. This analysis does not take into account skills that people may have gained from a previous job or other experiences.
+ The converse is also true. It may be that there are people employed in certain occupations whose particular job does not require all the skills that are important according to O*NET.
+ The analysis is restricted to sex assigned at birth due to the available data. It is not possible to study gender in the current demographic exploration. However, the questionnaire of the upcoming Census includes questions on both sex and gender.[79] This allows future iterations of this project to consider gender identities.

A FORECAST OF EMPLOYMENT AND SKILLS IN 2030

Based on the collected expert opinion, BII+E's forecast of employment in 2030 suggests that jobs that are service oriented, creative or highly technical are likely to grow in importance, driven largely by flexible cognitive and social skills and abilities. On the other hand, jobs in resource extraction and manufacturing may experience a decline in employment share due to trends like resource scarcity and the decreasing need for workers to complete routine tasks. This forecast points to areas within Canada's labour market where opportunities or risks may lie, and to the skills, knowledge, and abilities that may improve workers' resilience in the future. The occupations and skills that emerge from this analysis as likely to grow or decline in importance provide a potential picture of employment in 2030. This could help orient the design of training programs, policies, and tools around the skills that are projected to be important across a wide range of jobs.

This set of projections is meant to be complementary to other sources of labour market information. Where this forecast is largely in line with others, it reinforces that certain trends are likely. Where it departs, it highlights potential alternative trends and gaps in current knowledge that may need to be explored and addressed. This section highlights 1) the occupational groups projected to rise or fall in importance over the next decade, and 2) the skills, knowledge, and abilities behind these projections.

GROWING + DECLINING OCCUPATIONS

A third of workers are currently employed in occupations with a high probability of change, according to this forecast. Individuals in jobs projected to become more prominent in the labour market by 2030 make up 19% of total employment, while 15% work in jobs that experts expect will become less prominent in employment share. In general, occupations in health as well as natural and applied sciences are projected to grow, while those in manufacturing and utilities are projected to decline. The following section highlights the occupational groups with the highest probabilities of change. Most broad occupational categories are projected to experience both decline and growth in the employment share of their various occupations.

Figure 1 illustrates the number of workers in occupations with varying projections of growth. It reveals patterns that may help policymakers, educators, and service delivery organisations better target efforts by pointing to where experts expect growth. It also gives clear signals on the potential size of the impact. Over 2 million workers in the natural and applied sciences, in health, and in sales and services hold jobs strongly projected to grow. Notably, most sales and services occupations, employing over 2 million people, fall just under the threshold, but are not projected to decline. In fact, most occupations in this group are estimated to remain stable in the next decade. It is important to note that this graph only presents this forecast's growth estimates, which predict the portion of experts who may expect an occupation to grow in employment share. As a result, a low projection of growth does not translate into a high projection of decline. The full set of projections generated by this model are presented in Appendix D.

Box 6: Methodology recap 1

What is a projection?
A projection is an estimate of the probability that the experts surveyed for this analysis would have classified an occupation as growing or declining in *employment share* by the year 2030. This forecast provides projections for 485 Canadian occupations.

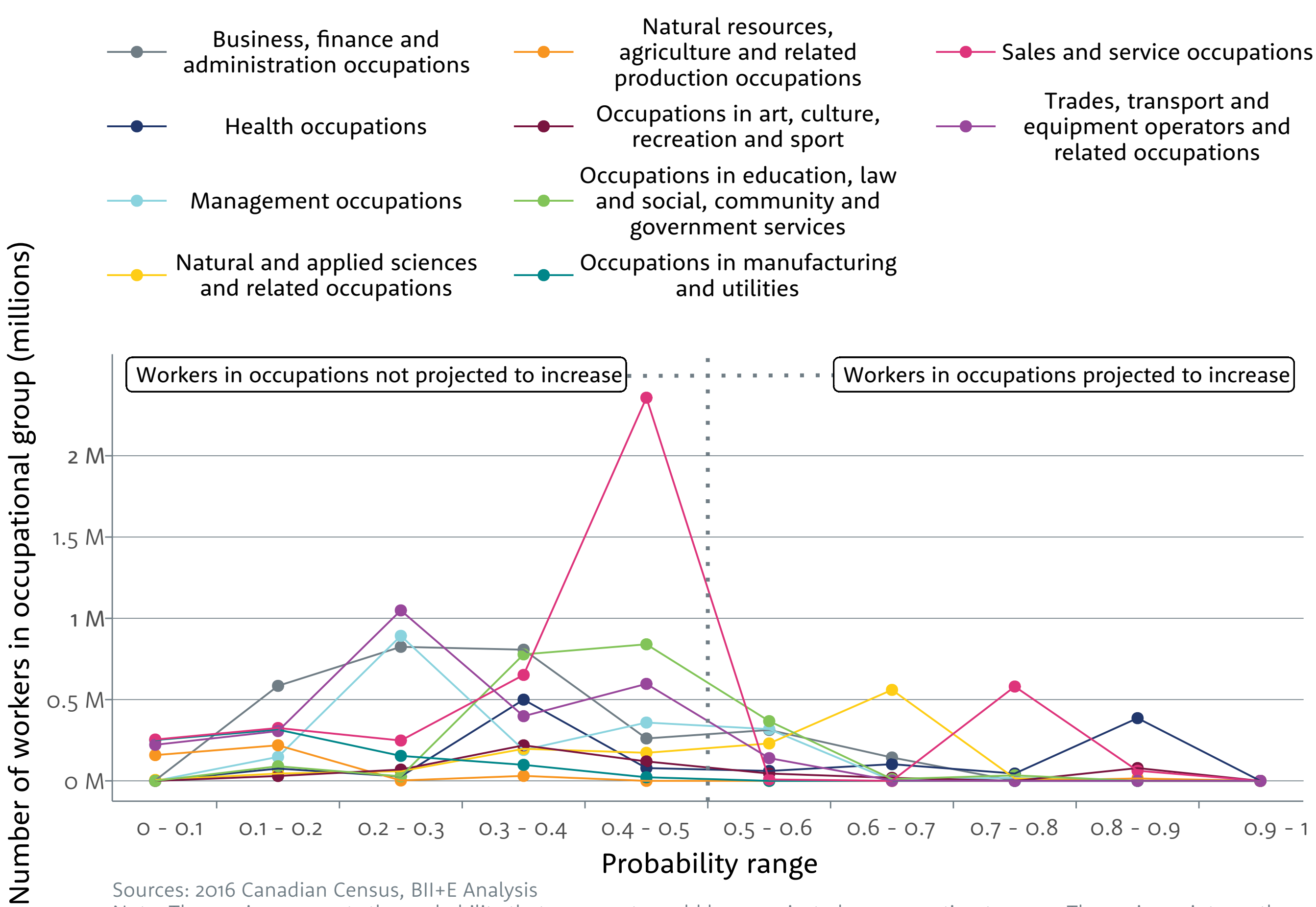
How are the projections generated?
Two sets of projections are generated by two distinct random forest models. One is designed to predict the probability that most experts classify an occupation as *growing* in employment share, while the other estimates the probability that most experts classify an occupation as *declining* in employment share.

What does it mean to grow or decline in employment share?
An occupation changes in terms of employment share when its portion of *total employment* grows or declines. This means that, depending on total employment, an occupation that declines in share by 2030 may actually employ more workers, and vice versa. This forecast focuses on employment share in order to better identify relative patterns among occupations independent of changes to total Canadian employment.

What does it mean for an occupation to be projected to grow or decline?
An occupation is projected to grow, in this analysis, when the model estimates that over half of the experts surveyed would classify it as *growing* in employment share (i.e. when it has a growth projection of over 0.5). An occupation that is not projected to grow is *not* necessarily projected to decline.
Conversely, an occupation is projected to decline when the model estimates that over half of the experts surveyed would classify it as *declining* in employment share (i.e. when it has a decrease projection of over 0.5). As is the case above, an occupation that is not projected to decline is *not* necessarily projected to grow.

Figure 1: **Broad occupational categories at a glance**

Distribution of the probability an expert would project growth, by broad occupational category



Sources: 2016 Canadian Census, BII+E Analysis
Note: The x axis represents the probability that an expert would have projected an occupation to grow. The major points on the graph indicate the number of workers within each broad occupational category who work in an occupation in each probability range.

Growing + declining occupations at a glance

Workers in jobs expected to grow have an average employment income of $62,430 and 45% of them are employed in either Healthcare, Professional services, or Accommodation and food services industries.[80] [81] Sales occupations have one of the highest portions of people in growth occupations, as well as many in occupations marginally under the cut-off, suggesting overall resilience. On the other hand, individuals in occupations projected to decline have a significantly lower average income of $40,380 and 46% of them work in Manufacturing, Construction, or Agriculture. The educational gap between the two groups is also significant. Almost half of workers (43%) in growing occupations have a bachelor's degree or higher, compared to only 13% of those in occupations projected to decline in importance.

Notably, the occupational groups most projected to grow have a relatively high probability estimate, while many of their counterparts are closer to the 50% cut-off. This difference in the forecast results indicates a higher level of agreement among experts regarding the occupations projected to grow in share versus those projected to decline in share.

Occupational groups projected to grow in employment share by 2030[82]

The following 10 occupational groups have the highest chance of being classified as growing in share of employment by workshop experts.

Note: This projection is based on skill, ability, and knowledge trait composition, but does not provide information about the magnitude of growth. It is important to note that if an occupation group is not identified as likely to increase in share by experts, it does not mean that they would label it as declining. They may have also identified it as being likely to remain constant.

The projections indicate that at least 60% of workshop experts expect these occupational groups to increase their employment share by 2030. Together, these occupations accounted for 5% of total national employment in 2016 and most usually require postsecondary education, which may include a university or college degree, vocational education, or apprenticeship training.

The trends highlighted by experts as likely to drive change for certain occupations in the course of answering the survey questions can help explain some of the reasons behind these projections. These trends are identified in *Turn and Face the Strange* and *Signs of the Times*.

Table 3: **Summary of minor occupational groups with the highest growth projections**

Occupation group (NOC code)	Number of workers (2016 Census)	Percentage of employment (2016 Census)	Predicted portion of experts that project growth in share[83]	Canadian Occupational Projection System (COPS) projection
Supervisors in logging and forestry (821)	4,600	0.02%	83%	Increase
Professional occupations in nursing (301)	322,700	1.6%	81%	Increase
Pharmacists, dietitians and nutritionists (313)	49,895	0.2%	81%	Increase
Chefs and cooks (623)	300,660	1.5%	77%	Decrease
Creative designers and craftspersons (524)	61,125	0.3%	70%	Increase
Technical sales specialists in wholesale trade and retail and wholesale buyers (622)	78,640	0.4%	65%	Increase
Mathematicians, statisticians, and actuaries (216)	12,915	0.06%	64%	Decrease
Other engineers (including mining, geological, materials, and industrial engineers among others) (214)	60,880	0.3%	64%	Increase
Technical occupations in computer and information systems (228)	112,545	0.6%	61%	Increase
Librarians, archivists, conservators, and curators (511)	13,680	0.07%	60%	Increase

For example, supervisors in logging and forestry emerged as a small group with a high potential for growth. This may be a result of experts' consideration of trends related to environmental sustainability. In particular, the challenges posed by Resource Scarcity and the increasing incidence of Wildfires, Floods, and Mudslides were top of mind for participants when discussing occupations in resource extraction sectors. The projections show that environmental concerns may translate into a higher need for more managerial workers in these industries, but may not do so for other forestry occupations. Moreover, a close look at forestry supervisors reveals that all the foundational skills identified in the next section of the report are important for workers in this group and may partly drive the high expectation of growth.

Nurses, pharmacists, dietitians, and nutritionists emerge as occupations highly likely to grow. Based on demographic trends such as population aging and an increased demand for health services, experts may have anticipated a growth in demand for patient care. This may also be due to the relative immunity of tasks involving interpersonal skills to being automated, especially nursing occupations.[84] Some STEM occupations are also present and expected, with high technical requirements and a focus on applied sciences. These include engineering or computing. Like the healthcare occupations, they often require a bachelor's degree at minimum.

Chefs and cooks are unique, as they were directly considered by experts, while the projections of other groups are generated by the prediction model. Workshop participants anticipated that trends like Entrepreneurial Spirit and the emerging Cannabis Economy may have some of the biggest impacts on these occupations. The recent legalization of Cannabis may create significant growth in the food industry, creating change for cooks and chefs. In addition, the Entrepreneurial Spirit trend highlights the idea that entrepreneurship-related work may become a dominant career path, where workers in this occupation create their own opportunities rather than committing to a single employer in 2030.

Creative designers and craftspersons, with a higher than average employment share in 2016, are also well-poised to grow based on the forecast projections. This group stands out as an important artistic domain. Similar to chefs and cooks, experts considered graphic designers and illustrators, a subset of this occupational group, during the Vancouver session. They shared that in addition to Entrepreneurial Spirit, Mandatory Creativity—an emerging trend which posits that creativity could become critical for all workers, not just for the arts and design community—might be among the trends most likely to drive jobs in this occupation.

Workshop participants also rated technical sales specialists in wholesale trade, industrial and manufacturing engineers, and computer network engineers. Experts expected technological trends to play a large role in the case of these more technical occupations. In particular, AI Everything and Blockchain could increase the need for workers with these skills, as AI continues to impact and disrupt almost every industry, and Blockchain adoption changes the security and authenticity processes of important transactions in a variety of settings, from banking to voting. In addition, demographic trends like Tech Talent Immigration, a mechanism for Canada to address tech talent shortages, may fulfill the increased demand and count among the main forces behind employment growth for this occupational group.

This list is interestingly diverse, and reflective of a number of themes that have emerged in discussions about the future or work. It comprises occupations with strong STEM components (e.g., mathematicians, engineers, computer and information systems roles), occupations that require strong interpersonal skills (e.g., in sales and nursing), professions requiring judgement (e.g., supervisors, archivists), and those requiring creativity (e.g., chefs, creative designers). This highlights that training policies and programs should not focus on any one area of knowledge, skill, or ability to best prepare people for the future of work, but instead support skills development on multiple fronts.

Occupational groups projected to decline in employment share by 2030[85]

The following 10 occupational groups have the highest chance of being classified as declining in share of employment by workshop experts.

Note: This projection is based on skill, ability, and knowledge trait composition, but does not provide information about the magnitude of share decline. If an occupation group is not identified as likely to decline by experts, it does not mean that they would label it as growing. They may have also identified it as being likely to remain constant. In addition, a decline in share is not equal to job loss. In fact, if national employment grows, a decline in share could still entail an increase in an occupation's employment.

Many of the jobs comprising these occupational categories deal with resource extraction or processing, and some jobs may also involve a high degree of routine tasks. Notably, the probability of most of these occupational groups to be classified as declining is considerably closer to the cut-off (50%) than those most expected to grow. This lower average indicates a higher level of potential disagreement among experts when it comes to the future of these occupations. The public works and other labourers group exemplifies this. While the model predictions suggest that over 50% of experts may classify it as declining by 2030, they also indicate that one in three experts may classify it as growing. Where experts are predicted to have differing views on an occupation's likelihood to decrease, policy responses should be more

Table 4: **Summary of minor occupational groups with the highest decline projections**

Occupation group (NOC code)	Number of workers (2016 Census)	Percentage of employment (2016 Census)	Predicted portion of experts that project decline in share[86]	Canadian Occupational Projection System (COPS) projection
Fishing vessel masters and fishermen/women (826)	25,415	0.1%	91%	Decrease
Other workers in fishing and trapping and hunting occupations (844)	7,285	0.04%	86%	Decrease
Mechanical, electrical and electronics assemblers (952)	109,620	0.5%	73%	Decrease
Machine operators and related workers in chemical, plastic and rubber processing (942)	36,900	0.2%	72%	Increase
Underground miners, oil and gas drillers and related occupations (823)	28,455	0.1%	66%	Increase
Central control and process operators in processing and manufacturing (923)	24,195	0.1%	64%	Decrease
Machine operators and related workers in mineral and metal products processing and manufacturing (941)	51,115	0.3%	62%	Increase
Managers in agriculture, horticulture and aquaculture (082)	153,630	0.8%	60%	Decrease
Trades helpers and labourers (761)	217,060	1.1%	57%	Decrease
Public works and other labourers (762)	39,845	0.2%	56%	Decrease

cautious, and additional study and monitoring may be warranted.

As was the case for the occupations projected to grow, these projections can be partly explained by the trends highlighted by experts in *Signs of the Times* as being most likely to drive change. During workshop discussions, Resource Scarcity emerged as one of the biggest drivers of change for the Canadian labour market in the next decade, as it related to these occupations. For some jobs in these groups, such as fishermen and women, plastics processing operators, and underground miners, experts expected Resource Scarcity to affect employment significantly and negatively. The growing reach of AI and automation also emerged as factors that may significantly lower the demand for occupations in assembly, machine and process operation. This expectation is in line with previous studies, which indicate that current tasks are likely to be at least somewhat automated in the next 10-15 years.[87]

However, the labour challenges in these sectors and occupations are complex. Various other factors could contribute to a fall in their employment share, from the aging of the population in manufacturing jobs, to the highly regionalised nature of the work and recruitment challenges.[88]

Employment in 2030 + the Canadian Occupational Projections System (COPS)

Per its intent, this forecast offers a picture of future possibilities positioned as complementary to other forecasts. BII+E compared its projections to those published through ESDC's Canadian Occupational Projections System (COPS), one of the principal forecasts used by various governmental and research organisations. COPS is the primary set of national projections available and currently provides employment estimates to the year 2026.[89]

An analysis of this forecast with respect to COPS is necessary and useful, as it contributes to the current understanding of the future of work. It may reveal patterns previously undetected and mitigate potential gaps in knowledge. However, a comparison between the *Employment in 2030* projections and COPS is only possible at a directional level. While COPS provides employment estimates, this forecast provides only the probability that an occupation might increase in share of employment, as informed by expert opinion and skill composition. It provides no measure of a magnitude of change. As a result, the two sets are consistent when they both anticipate an increase or a decrease in employment share.

Comparing forecasts

At the occupational level, there are some discrepancies between the two sets of estimates.[90] Overall, 56% of the occupational projections agree with their COPS counterparts. This is consistent with the 53% rate of agreement for the 45 expert-rated occupations.[91] Given that participants were provided with the relevant COPS projections for each occupation during the workshops, these results suggest that the disagreement is deliberate. For example, while this forecast highlights chefs and cooks, as well as mathematicians, statisticians, and actuaries, as projected to grow, COPS estimates that the employment share of these professions is expected to decrease. On the other hand, COPS has more optimistic estimates for machine operators as well as underground miners and drillers than those presented in this report.

When looking at broad occupational categories, more interesting comparisons and patterns emerge. Both the *Employment in 2030* forecast and that of the Government of Canada strongly expect growth for occupations in health as well as natural and applied sciences occupations. Sales and service occupations are also expected to grow over the next decade. Yet, as tables 5 and 6 show, there are discrepancies. COPS projects that occupations in manufacturing and utilities or natural resources may increase in employment share by as much as 20%, while this forecast indicates that they may be expected to decline. The reverse is true of occupations in art, culture, recreation, and sport. BII+E's projections indicate that most experts would expect occupations in these groups to perform strongly and grow, yet COPS estimates signal a decline in employment share.

The existence of discrepancy indicates that the mixed-method approach used for this project provides additional information to other forecasts, and may capture structural changes or factors that are harder to accommodate in systems like COPS. Analyzing the reasons behind these differences is beyond the scope of this study, but necessary in future work. Awareness of these sources may point to occupations that are more exposed to structural changes in the coming decade, and require additional attention on the part of governments, policymakers, and service providers as they prepare for the future of the Canadian workforce.

Table 5: **Broad occupational categories ranked by *Employment in 2030* projections**
From most likely to be projected to increase in share, to most likely to be projected to decline

Health occupations
Natural and applied sciences and related occupations
Occupations in art, culture, recreation, and sport
Sales and service occupations
Occupations in education, law and social, community and government services
Management occupations
Business, finance, and administration occupations
Trades, transport, and equipment operators and related occupations
Natural resources, agriculture, and related production occupations
Occupations in manufacturing and utilities*

Note 1: The E2030 projection for broad occupational categories is calculated by averaging the projections of all the occupations included within it, and weighing them by employment.

Table 6: **Broad occupational categories ranked by the magnitude of projected change in employment share according to COPS**
From highest expected growth to highest expected decline

Natural and applied sciences and related occupations
Health occupations
Natural resources, agriculture, and related production occupations
Sales and service occupations
Occupations in manufacturing and utilities
Trades, transport, and equipment operators and related occupations
Occupations in education, law and social, community and government services
Business, finance, and administration occupations
Occupations in art, culture, recreation, and sport
Management occupations*

*Note: * indicates a broad occupational category that is projected to decline in employment share.*

Growing + declining industries

This forecast suggests that the majority of Canada's industries will continue to be important into the future. All but four major industries employ less than 25% of their workers in jobs projected to decline in employment share, indicating a general employment resilience. The accompanying industry graphs show the portion of workers in each industry that are in occupations projected to grow or decline over the next decade. They also show that, across industries, men are more likely to work in occupations projected to both grow and decline.

It is important to note that the projections are directional (indicating increase or decrease) and do not include a measure of the magnitude of the projected changes. While nothing can be concluded regarding overall industrial employment, this analysis suggests that some industries are more likely than others to experience change, according to experts.

Box 7: Industries most likely to experience change

Industries with the largest portion of workers in occupations projected to grow in employment share:

1. Professional, scientific, and technical services
2. Information and cultural industries
3. Utilities
4. Health care and social assistance
5. Accommodation and food services

Industries with the largest portion of workers in occupations projected to decline in employment share:

1. Agriculture, forestry, fishing, and hunting
2. Manufacturing
3. Mining, quarrying, and oil and gas extraction
4. Construction

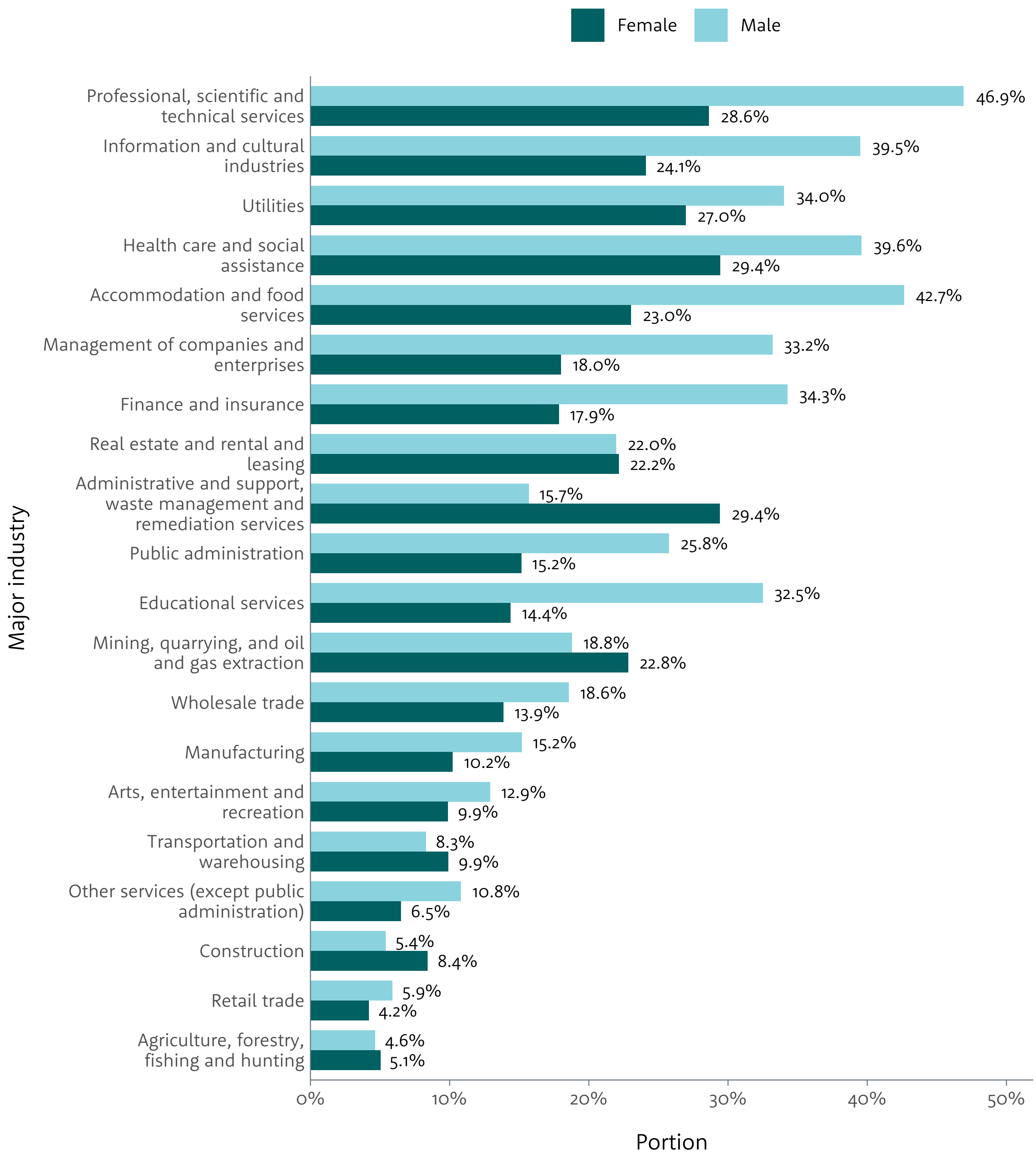
As shown in Figure 3, most industries have less than a quarter of workers in jobs projected to decrease. This result implies that most industries are set to be fairly resilient, but some emerge as particularly stable. The sectors that have a very low portion of workers in occupations projected to either grow or decline include: arts, entertainment, and recreation; retail trade; and other services (except Public Administration).[92] Even within these relatively stable sectors, women remain in a position of resilience and are less likely to hold jobs that are projected to decrease.

Other industries, however, are projected to experience significant disruption, with both a high number of workers in occupations projected to grow and a high number in those projected to decline in employment share. Some have the potential to expand in employment according to this forecast, including: professional, scientific and technical services; healthcare and social assistance; accommodation and food services; and informational and cultural services. Utilities and finance and insurance follow closely. These are industries with a high degree of service orientation and technical expertise, employing a high portion of workers in jobs projected to increase and low proportion in jobs expected to decrease. Women comprise most of the workforce in these industries and account for 64% of all workers. However, men in these industries are 15.8 percentage points more likely than women to be in growing occupations, compared to an average of 2.3 percentage points across all industries.

Other industries bear a higher risk of being impacted by the declining employment share of certain occupations, based on the expert-driven projections. Specifically, sectors which employ over a quarter of their workers in occupations projected to decline are: agriculture, forestry, fishing and hunting; manufacturing; mining, quarrying, and oil and gas extraction; and construction. The portion of agriculture workers that are in occupations projected to decrease is 61%. A deeper look reveals that 21.5% of workers in this industry are general farm workers, an occupation the model predicts 52% of experts would rate as likely to decrease in employment share; this specific occupation is likely

Figure 2: **Industries at a glance**

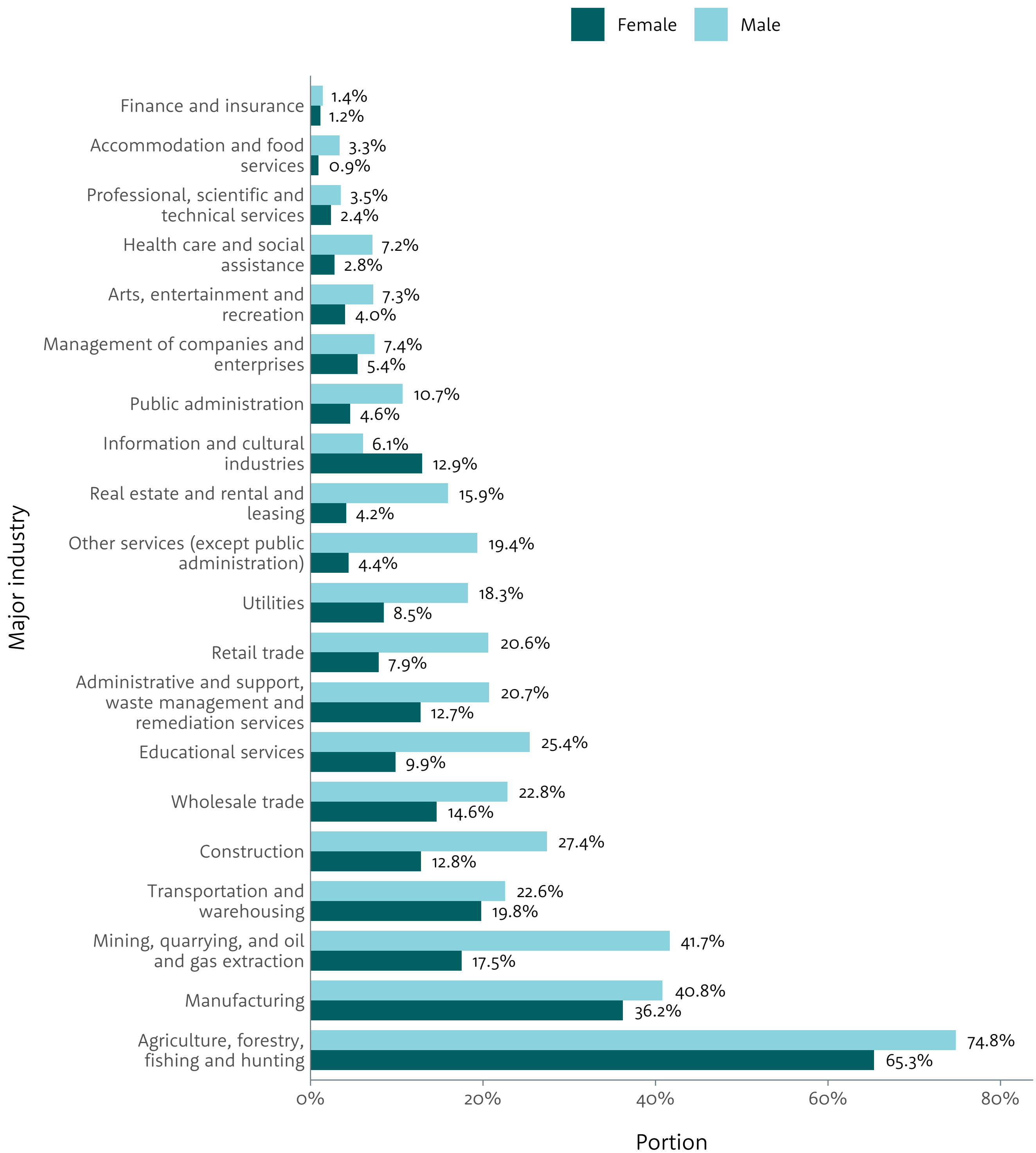
Workers in occupations projected to grow, by major industry and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Figure 3: **Industries at a glance**

Workers in occupations projected to decline, by major industry and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

driving some of the risk ascribed to the agricultural sector. Given the historical decline of agriculture as a high-employment industry, this expected decline is not surprising.

In the case of manufacturing, 43% of the workforce is employed in occupations projected to decline. While this portion is substantially lower than the estimate for the agricultural sector, it remains significant, and is comparable with the estimates for the mining and oil extraction industries. For both agriculture and manufacturing, 77% of those working in these industries are men, but the portion of men and women in jobs projected to decrease in share is comparable.

As previously described, for the purposes of this analysis BII+E defines an occupation as growing or declining if the model predicts that more than 50% experts would have classified it as such. However, some occupations just meet the 50% threshold. For example, the majority of the manufacturing workforce includes a number of occupations that just meet the 50% threshold that classifies them as declining. The same is true for general farm workers employed in the agricultural sector. While these projections do point to potential declines, they also suggest disagreement among experts about the likelihood of these declines and about these industries' resilience.

For those industries projected to experience significant changes, policy action may be needed to support them. Focused investments could support employer and worker transitions for industries employing a high number of individuals in occupations projected to decline in employment share by 2030. For sectors well-poised to grow, investments may help ensure a robust talent pipeline. For industries expected to experience both growth and decline in different occupations, there may be particularly promising opportunities to help workers transition between jobs within the same industry.

THE SKILLS, KNOWLEDGE, AND ABILITIES FOR 2030

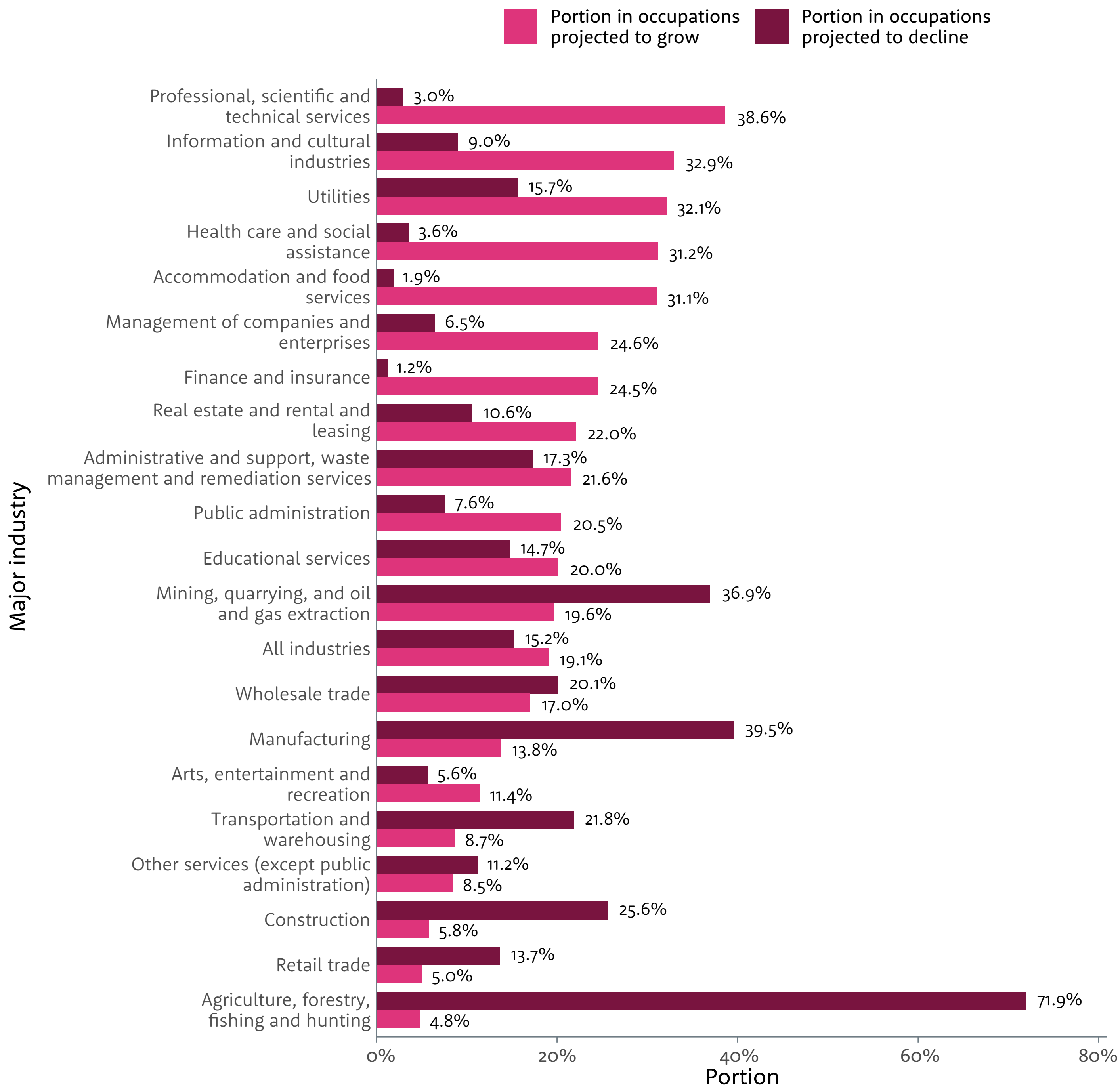
Amidst changes to the economic landscape, the importance of core cognitive and social skills and abilities is increasing across the economy. Above and beyond what technology can deliver, employers need workers with strong social acuity, good communication skills, creativity, judgment, and problem solving. Some skills are likely to be valuable across the labour market and, as such, foundational. Some will be more specific to particular sets of occupations, while others still will complement specific areas of knowledge.

BII+E identified five foundational skills and abilities through this forecast. They are exceptionally important for occupations currently projected to grow, and are likely to be essential for the resilience of both new and incumbent workers in 2030. These foundational traits are key determinants of growth across sectors and job types, suggesting that regardless of how specific occupations change in the future, these skills are forecast to be in demand across the economy.

Beyond these five foundational skills and abilities, valuable complementarities arise in different contexts. Adding a particular skill or ability can increase the probability of an occupation being projected to grow, as some traits can integrate with others particularly well. The skills that best complement some of the characteristic traits of a broad group of occupations provide a possible picture of the skill sets that may grow in importance for large portions of the workforce. When these complementarities are considered in the context of areas of knowledge, they can highlight the skills that may help workers, educators, and students best leverage their existing education. For example, this forecast indicates that practical negotiation skills taught alongside sociology and anthropology courses may maximise the benefits of this knowledge in the labour market, among others.

Figure 4: **Industries at a glance**

Workers in occupations projected to change, by major industry and direction of change



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.
Note 3: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 4: Each bar represents the portion of a demographic group that is in a declining occupation.

Foundational skills and abilities

Five skills and abilities emerge as foundational: **fluency of ideas**, **memorization**, **instructing**, **persuasion**, and **service orientation**. The first two traits are cognitive abilities, the next three are social skills, and all prove highly relevant across occupations. Each of these traits is so essential that its absence makes it very unlikely for an occupation to be classified by experts as growing. On the other hand, when these attributes are important to an occupation, they always improve its growth projection. The presence of all five, on average, means an occupation *will* be projected to grow in employment share.

In order to be considered foundational, a trait must add to an occupation's projection at least 95% of the time it appears in the random forest, and must do so over several runs of the model.[93]

These strict criteria ensure that the traits are useful, transferable, and necessary regardless of any others that may be required by a specific profession. In addition, the foundational traits identified echo the wider field of research, including recent BII+E work, where there is growing evidence of the importance of diverse social and cognitive skills and abilities.[94] [95] [96] Policymakers should consider integrating these into official skill assessment, funding priorities, and measurement frameworks, such as ESDC's Essential Skills, for two important reasons: they are particular to the Canadian context, and they are likely to rise in importance and value.

This analysis focuses on the results observed from the increase model as no other skills, abilities, or knowledge traits had a similar consistency of impact when examining occupations more likely to be projected to decline.

Box 7: Foundational and high-impact traits

Foundational traits

Foundational traits prove the most important among all the considered skills, abilities, and knowledge areas. They are virtually necessary for an occupation to be projected to grow and they consistently increase the projection.

To identify foundational traits, the random forest model separates the occupations that have low scores from those that score average or higher, rather than identifying the occupations that have particularly high scores. As a result, an occupation needs a minimum importance score in these attributes to be of benefit, but is not rewarded heavily for higher scores.[97]

1. Fluency of ideas
2. Memorization
3. Instructing
4. Persuasion
5. Service orientation

Other high-impact skills

Other skills, abilities, and knowledge areas also proved impactful in this forecast, even if they did not meet the stringent requirements to be classified as foundational.[98] From knowledge of fine arts to technology design, systems evaluation, and originality, 11 other attributes are also projected to be highly relevant, transferable, and useful across occupations for Canada's 2030 workforce.

1. Originality
2. Systems Evaluation
3. Technology Design
4. Systems Analysis
5. Visualization
6. Active Listening
7. Customer and Personal Service
8. Installation
9. Number Facility
10. Philosophy and Theology
11. Fine Arts

Foundational trait #1: Fluency of ideas

The ability to generate a number of ideas on a topic, or to brainstorm. The number of ideas generated is important, not their quality, correctness, or creativity.[99]

Fluency of ideas is a highly valued ability across most occupations (70%), but is particularly important in the creative industries and the sciences. Of all the skills, abilities, and knowledge traits, a high fluency of ideas score contributes the most to an occupation being projected to grow in employment share. In fact, having a relatively high importance score in fluency of ideas seems to be necessary for an occupation to receive a growth projection.

Foundational trait #2: Memorization

Memorization is the ability to remember information such as words, numbers, pictures, and procedures.[100]

At first glance, this result is surprising since the need to memorize can be, at times, easily automated or outsourced. However, knowing principles, names, and processes, as well as being able to recall them in specific situations, is key for any job. Healthcare occupations where medical procedures are commonplace are an excellent example. Even in occupations where abstract thinking is predominant, such as for a computer developer, successful employees often memorize a programming language or other technical information. A certain level of memorization may enhance and lay the basis for critical and analytical thinking.[101] [102] [103] Unlike the other foundational skills and abilities, most occupations do not require memorization (70%), but it always has a positive impact.[104] Occupations where it is required tend to fall in education, law and social, community and government services, or natural and applied sciences.

Foundational trait #3: Service orientation

Service orientation measures how important it is to actively look for ways to help people, from customers to colleagues.[105]

This skill is highly important in most occupations, but particularly so for those with a high degree of interaction with the public or with clients. Service orientation is unique among the foundational traits in that, on average, it requires a higher importance score in order to contribute to a growth prediction.[106] This suggests that a service focus is somewhat important for almost all occupations, but stands out in sales, services, and healthcare, some of the areas with the highest growth projections in this forecast.[107]

Foundational trait #4: Instructing

The skill of teaching others how to do something.[108] *It can be thought of as coaching, sharing information, or training.*

In this analysis, instructing is considered important for most occupations (63%). This is especially true after some career progression, as there are no management occupations where instructing is not considered necessary.[109] This points to the importance of developing this skill for longer-term success. The average projection for occupations where instructing is important is 19 percentage points higher than the estimates for those where this is not the case.

Foundational trait #5: Persuasion

This skill measures one's aptitude for changing others' minds and behavior.[110]

This is one of the most relevant social skills in the workforce, as it is important to 60% of occupations. Similar to instruction, there are no management occupations that do not consider persuasion to be relevant, as it relates directly to influencing others' performance and behaviour.[111] Persuasion has one of the highest positive impacts. An occupation that requires persuasion is 25 percentage points more likely to be classified as increasing in employment share than one without it.

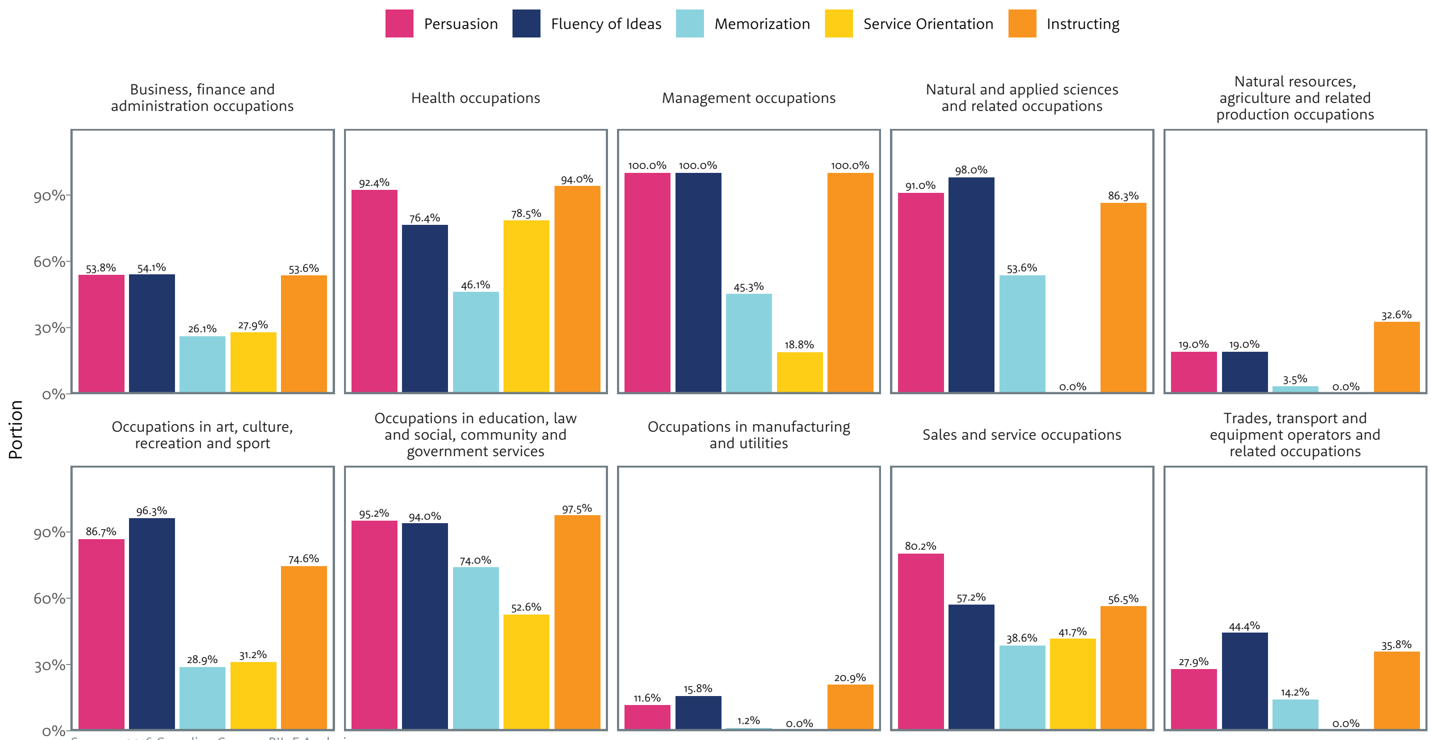
Table 7: **Foundational traits and their influence**

Foundational skill or ability	This skill or ability is important for... (% of occupations)	An occupation with this skill or ability is more likely to be projected to increase by... (percentage points)
Fluency of ideas	70	21
Memorization	30	22
Service orientation	74	25
Instructing	63	19
Persuasion	60	25

Who has the foundational skills and abilities today?

Figure 5: **Foundational traits at a glance**

Portion of workers in occupations requiring each foundational skill and ability, by broad occupational category



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: A worker is considered to have a foundation skill or ability if they are in an occupation where the importance score for that skill is greater than 2.5.
Note 2: Each bar represents the portion of a broad occupational category that has a foundational skill or ability.

Figure 5 shows the portion of workers in an occupation that requires a foundational skill or ability by broad area of employment, according to the 2016 Census. As previously discussed, most occupations require a combination of these foundational traits. Occupations in education, law, as well as social, community, government services, and health, however, require all five. In other broad occupational categories, the majority of employees are in occupations that require memorization and service orientation to a lesser extent.[112]

Workers in manufacturing, utilities, or natural resources and agriculture are the exception. Few are in occupations that require any of the foundational skills or abilities. As explored in Section 6.1, Growing + declining occupations, these are also the types of occupations for which experts are least likely to project growth. As a result, workers in these industries and occupations warrant special attention over the next decade. While having any number of these foundational skills and abilities does not guarantee a person will either avoid job disruption or be employed in 2030, having and developing them will very likely increase a worker's resilience to labour market changes.

Complementary and augmenting traits

Complementary skills: By broad occupational category

While foundational attributes help inform potential workforce- and education-wide interventions, some skills, abilities, and knowledge areas may also prove to be *conditionally* useful in certain occupational contexts. A skill or ability that increases the likelihood that experts rate a healthcare occupation as growing may not do the same for a business occupation. For a more granular analysis, Table 8 identifies the traits that may be most useful given the skills required within a group of occupations.

Table 8: **Key and complementary attributes by broad occupational category**

Category	Key Attributes[2]	Complementary Attributes[3]
Management occupations	Administration and management Oral expression Oral comprehension	Psychology*** Fine arts*** Social perceptiveness**
Business, finance, and administration occupations	English language Oral comprehension Written comprehension	Originality** Learning strategies** Medicine and dentistry**
Natural and applied sciences and related occupations	Oral comprehension Problem sensitivity Critical thinking	Computers and electronics*** Visualization*** Technology design***
Health occupations	Customer and personal service Oral comprehension Oral expression	Visualization** Design** Mathematical reasoning**
Occupations in education, law and social, community and government services	Oral expression English language Oral comprehension	Quality control analysis** Troubleshooting * Counselling and therapy*
Occupations in art, culture, recreation, and sport	Oral expression Oral comprehension Active listening	Education and training*** Mechanical knowledge** Visualization**
Sales and service occupations	Customer and personal service Oral expression Speaking	Visualization** Design** Far vision**
Trades, transport and equipment operators, and related occupations	Near vision Problem sensitivity Oral comprehension	Computers and electronics*** Technology design*** Wrist-finger speed**
Natural resources, agriculture, and related production occupations	Multi-limb coordination Problem sensitivity Control precision	Computers and electronics*** Technology design*** Installation**
Occupations in manufacturing and utilities	Production and processing Near vision Problem sensitivity	Computers and electronics*** Technology design*** Wrist-finger speed**

Note 1: Foundational skills and abilities are not included in this analysis since they always contribute to an occupation's projection of growth, regardless of its other attribute scores.
Note 2: The key attributes are those important for all occupations in a broad occupational category. The attributes presented are the top 3.

Note 3: The number of asterisks denotes the consistency of the attributes over several runs of the model. Attributes with 3 stars arise as complementary 15 out of 20 times or more, those with 2 stars at least 10 times, and those with one are less frequent and may occur as seldom as 5 times.

For each broad occupational category, Table 8 highlights three of its key attributes which are then used to identify potential complementary traits.[113] For example, all occupations in management have high importance scores in administration and management, oral expression, and oral comprehension. Given that knowledge of administration and management is important within an occupation, a high score in psychology will, almost always, increase its growth projection in the forecast. The complementary attributes vary from group to group, with only a few commonalities across fields of work. However, within each occupational group, the forecast indicates that the complementary attributes may grow in importance over the next decade.

These complementarities could inform a number of initiatives. They can help program designers create training programs that aim to help specific workers, such as those sponsored by industry associations or unions and those aimed at workers experiencing disruption. Other than influencing retraining and transitions, they also have the potential to guide formal educational curricula, leveraging existing educational infrastructure to increase the resilience of future workers.

Augmenting traits: By knowledge area

No field of knowledge emerged as foundational or consistently important across occupations. This is not surprising, given that knowledge traits such as mathematics or geography are often tied to a specific context or industry. However, when taken in combination with certain skills and abilities, knowledge traits can have a considerable effect and significantly improve an occupation's projection of growth.

In line with previous research, these results point to the need to not only look at individual worker traits, but also bundles of skills, abilities, and knowledge traits in order to plan for resilience.[114] These augmenting traits could help policymakers, designers, and providers of education and training pinpoint the skills that could be taught alongside current curricula in order to prepare students for the workforce in 2030. Ensuring the integration of these traits into each field of education could allow current and prospective workers to harness their knowledge base to their best advantage.

Important knowledge areas

The impact of each knowledge trait on an occupation's projection of growth can be positive or negative, depending on the other skills and abilities with which it is paired. This analysis identified augmenting traits for all available knowledge areas, which are presented in Appendix C: Structural Skill Influence Analysis. In order to explore some of these relationships further, the profiles in Table 9 delve into three knowledge areas that are particularly important for classification decisions in the forecasting model.[115]

Table 9: **Augmenting traits for select knowledge areas**

Augmenting attributees	Knowledge area
Social perceptiveness*** Speech clarity*** Therapy and counseling**	Chemistry
Problem solving*** Critical thinking*** Systems evaluation***	Computers and electronics
Static strength** Category flexibility** Written expression**	Law and government

Note 1: Foundational skills and abilities are not included in this analysis since they always contribute to an occupation's projection of growth, regardless of its other attribute scores.
Note 2: The number of asterisks denote the consistency of the attributes over several runs of the model. Attributes with 3 stars arise as complementary 15 out of 20 times or more, those with 2 stars at least 10 times, and those with one are less frequent and may occur as seldom as 5 times.

Chemistry

Chemistry encompasses the knowledge of the chemical composition, structure, and properties of substances, along with the chemical processes and transformations that they undergo. This includes uses of chemicals and their interactions, danger signs, production techniques, and disposal methods.[116]

A relatively high importance score in this trait will contribute to an occupation's growth projection most of the time, but this effect is always positive if social perceptiveness, speech clarity, or therapy and counseling are also required.[117] On the other hand, if memorization and number facility are not important for an occupation, chemistry is likely to have a negative impact on the final projection. Knowledge of chemistry proves very beneficial to growth projections in the case of pharmacists and chemical engineers, but less useful for agricultural representatives and consultants.

Computers and electronics

Knowledge of computers and electronics involves an understanding of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.[118]

Knowledge of computers and electronics is a valuable trait. It usually improves an occupation's projection of growth, and is especially beneficial when augmented with critical thinking, problem sensitivity (the ability to tell when something is wrong or is likely to go wrong), and systems evaluation skills.[119] This trait contributes to the growth projections of computer engineers and web designers/developers. For certain occupations, however, a high importance score can lower the probability of projected growth in employment share.[120] If knowledge of computers and electronics has a negative influence, it lowers the occupation's projection by 43 percentage points on average. This outcome is particularly salient when there are low originality and systems evaluation requirements, which often occurs in administration occupations. To a certain level, this knowledge trait may be associated with routine task knowledge, the demand for which is decreasing.[121] This may be the case for administration officers and assistants.[122]

Law and government

Knowledge of laws, legal codes, court procedures, precedents, government regulations, executive orders, agency rules, and the democratic political process.[123]

Knowledge of law and government is unique when compared to the previous knowledge traits. A high importance score usually has a negative influence on an occupation's growth projection.[124] As a result, occupations that require knowledge of law and government are less likely to be projected to grow in the future. However, if this area of knowledge is combined with high scores in written expression, static strength, or category flexibility (the ability to generate or use different sets of rules for combining or grouping things in different ways), then knowledge of law and government always has a positive influence. This is seen in the projections for public, environmental, and occupational health and safety inspectors, as well as for fire chiefs and senior firefighting officers.

DEMOGRAPHIC IMPLICATIONS

Unless appropriate supports to help people navigate a changing labour market are established, a future in which different skills and occupations' employment shares are rising or falling is likely to position some to succeed while putting others at a disadvantage. In expanding this forecast to current demographic data, it becomes evident that risks, resilience, and opportunities are unevenly distributed across Canada's geography and population. Even at a high level, the landscape is unequal.

Additionally, Canada's population is experiencing a shift bound to ripple through the workforce. By 2036, the Indigenous population could grow by as much as 40%, first-generation immigrants may represent up to one-third of the country's population, people of colour may account for as much as 40% of the core working population, and population aging will dramatically shift the country's dependency ratio. [125] [126] [127] [128] This coming transformation makes it vital to understand where different groups stand and how they may be impacted in the future.

While this analysis examines data from the 2016 Census and does not include a measure of the future distribution of workers who will be entering the market in 2030, it provides some helpful signals:

+ Workers who have completed a bachelor's degree and those in the highest income quartiles are *significantly more* likely to be in occupations projected to increase than individuals with any other level of education or in lower income quartiles.

+ Those who identify as visible minorities or first-generation immigrants are *more* likely than their counterparts to be employed in occupations projected to grow. However, they are also marginally less likely to be in jobs that require the skills and abilities identified as foundational.

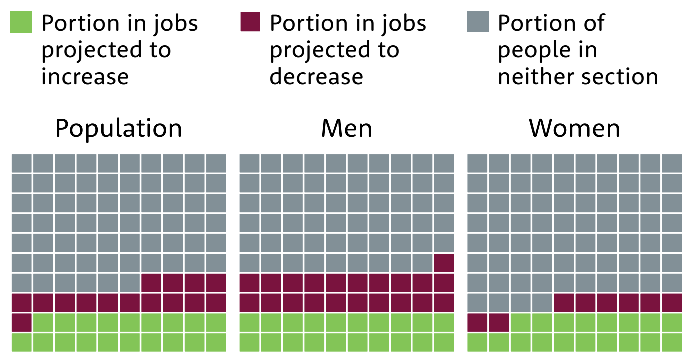
+ Those who are Indigenous are *much more* likely to work in occupations projected to decrease than occupations projected to grow. In particular, Indigenous men are disproportionately represented in occupations projected to decline in employment share.

+ Male workers are *significantly more* likely to work in occupations projected to grow *and* decline in employment share. A remarkably low percentage of female workers are employed in occupations that are projected to decline, possibly due to the higher likelihood of needing the five fundamental skills and abilities in their current jobs. These results may suggest that women are in more stable occupations compared to men and could therefore experience both fewer opportunities and fewer risks in the future.

Table 10: **Projections at a glance**

	Population*	Men*	Women*
Portion in jobs projected to increase	19.1%	202.%	17.9%
Portion in jobs projected to decrease	15.2%	21.7%	8.4%
Portion of people in neither section	66.6%	59.1%	74.5%

**Estimates do not add up exactly to 100% due to the use of separate models to predict increase and decrease classifications by experts.*



The data used in this analysis offers limited insight into potentially important intersectionalities. Multiple factors may affect the distributions presented in this section. For example, in the case of visible minority, Indigenous, immigrant, or young workers, formal educational credentials are likely to be correlated to some of the results. In addition, risk and precariousness may be due to the jobs people hold, the double impacts of income and education level, or a combination of circumstances beyond workers' skills. The following section provides snapshots of who is (and who is not) currently employed in occupations that experts would consider likely to grow, and who has the foundational skills and abilities identified as important for growth by: educational attainment, visible minority group, immigration experience, Indigenous identity, and income quartile. For each, the potential for opportunities, resilience, and risks is discussed.

Box 8: Methodology recap 2

When is an occupation projected to grow or decline?

An occupation is *projected to grow or increase* when the estimate of the increase model exceeds half (0.50). As such, a growth projection of 0.70 indicates that 70% of experts surveyed would have expected the occupation to have a greater share of employment in 2030 than it currently holds. Conversely, an occupation is *projected to decrease or decline* when the estimate of the *decrease* model exceeds half (0.50). A decrease projection of 0.70 indicates that 70% of experts surveyed would have expected the occupation to have a lower share of employment in 2030 than it currently holds.

Notably, a declining share does not necessarily imply fewer jobs. If national employment grows over the next decade, an occupation with a lower employment share may still have a higher number of people employed. Changes in share are indicators of the relative importance of an occupation in terms of employment in the labour market.

What are the sources for the demographic analysis and its limitations?

All data used for demographic analysis is from the 2016 Census of Population. It consists of occupational employment statistics, segmented by region or other demographic characteristics such as sex, age, income, period of immigration, belonging to a visible minority, and Indigenous identity. Due to data availability, the only intersectionality considered in this analysis is sex assigned at birth. This data is imperfectly used to categorise men and women due to the lack of comprehensive national information on workers' genders. A future iteration of this study could address this limitation, using the upcoming updated Census data.[129]

Each demographic profile is a snapshot, where only specific attributes are in focus. Since there is no comprehensive analysis of the factors that may interact with each of the demographic identities, any correlations present should not be interpreted as causal.

What are the sources for the skills analysis and its limitations?

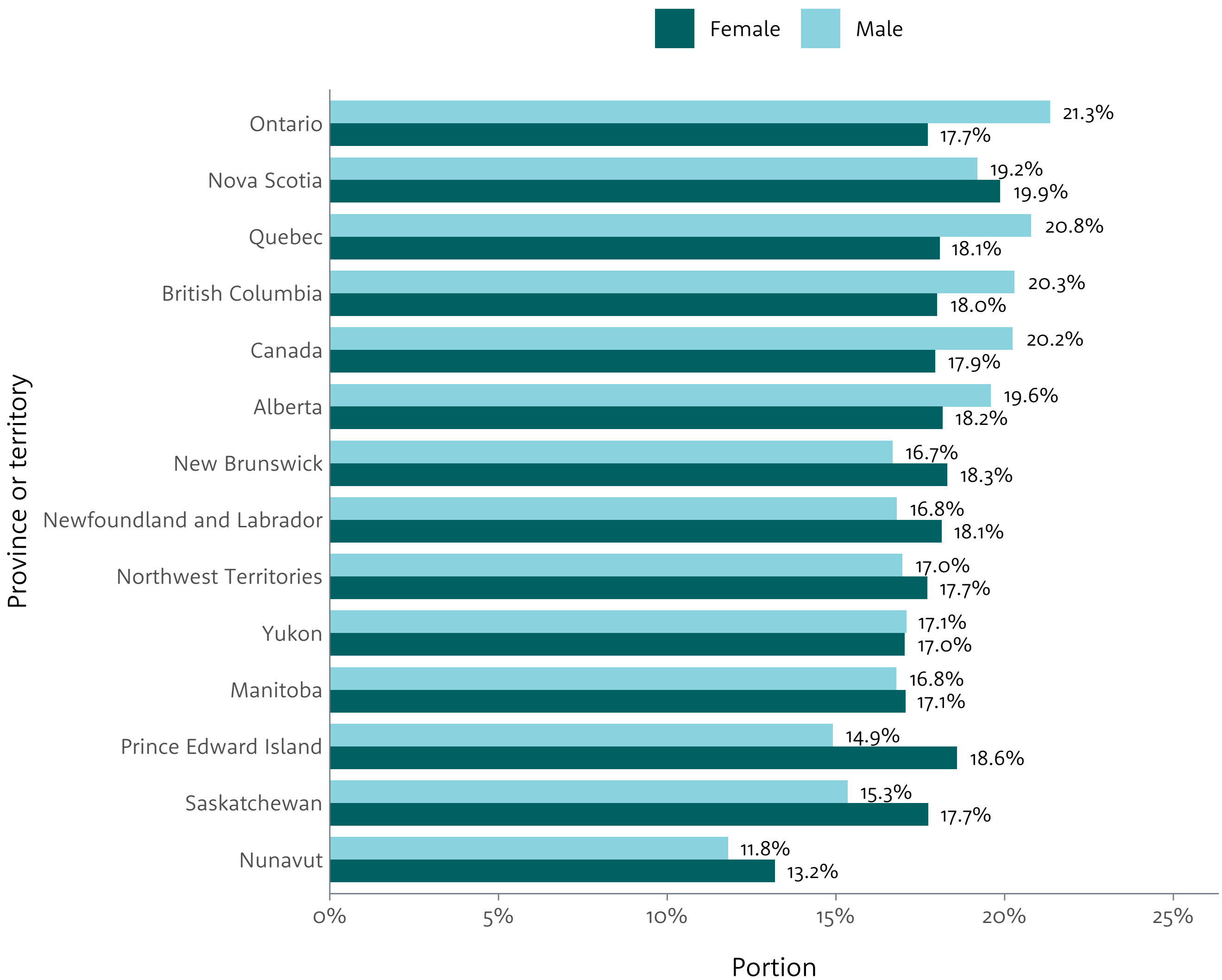
BII+E's analysis examines who has the skills and abilities that may prove to be foundational for resilience and growth in the next decade. This approach considers who is currently in an occupation where these are important according to O*NET, and could therefore be inferred to have them. It aims to provide some insight into the groups that might be better positioned for the future and those that might need more support.

Lacking career history or skills assessment data on workers, the skills, abilities, and knowledge attributes important to their current occupation are a useful proxy. People may, however, possess skills unrelated to their current occupation. Alternatively, people who hold jobs in occupations where certain skills or abilities are important may not have them, or may not apply them to their particular position.

WHICH WORKERS ARE IN OCCUPATIONS PROJECTED TO GROW + DECLINE?

By province or territory

Figure 6: **Regions at a glance**
Workers in occupations projected to grow, by province or territory and sex

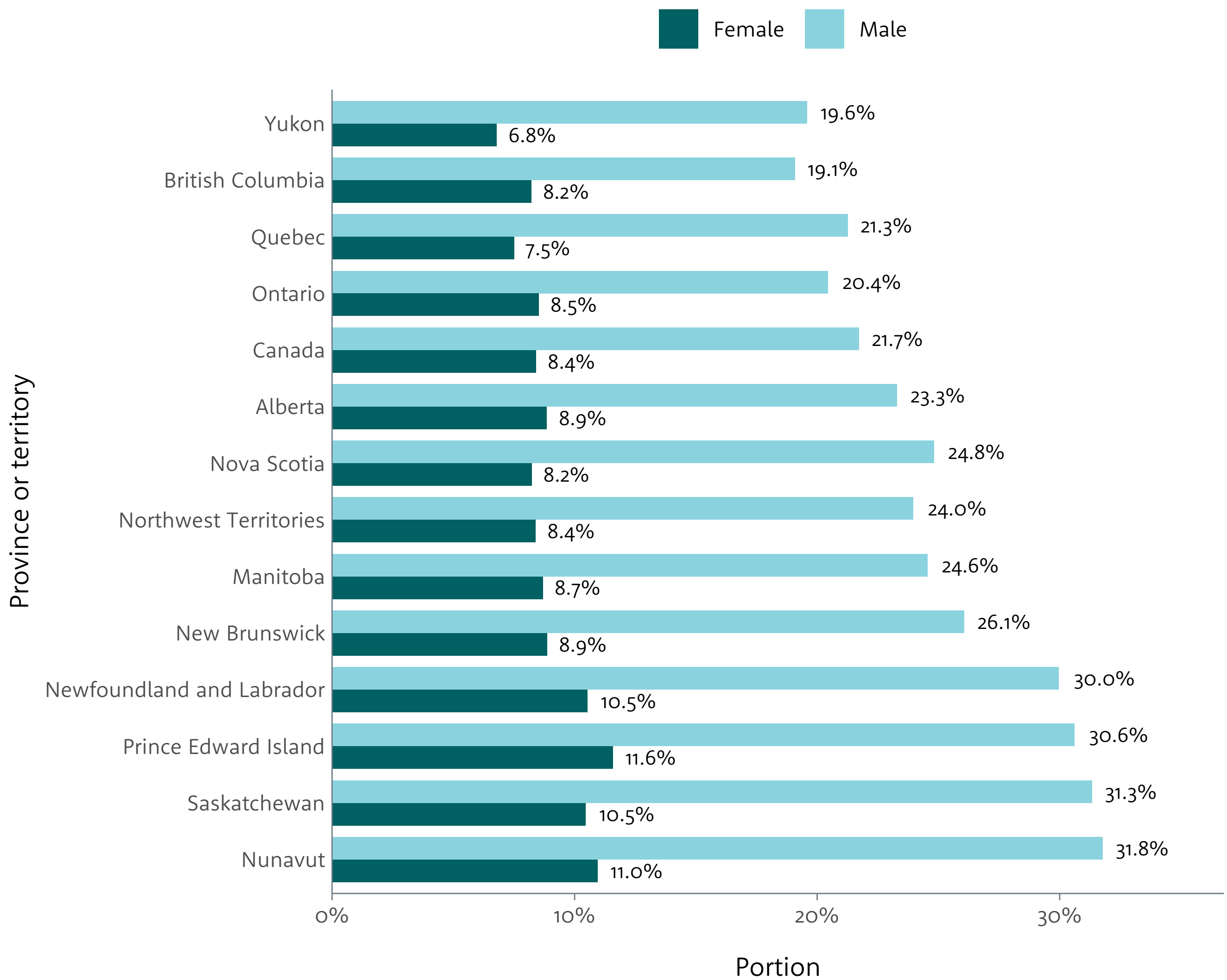


Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Most provinces are comparable in terms of the proportion of workers in occupations projected to grow, with at least 12% of their workforce employed in these potentially expanding occupations. While Ontario and Quebec lead in this regard, there are no identifiable regions that are obviously better poised to grow. Nunavut, however, stands out with its substantially lower numbers, well below the national average.

Workers in Nunavut and Saskatchewan are not only less likely to be employed in occupations projected to grow, they also have a much higher likelihood of working in declining ones, particularly when compared to those in Yukon or British Columbia. As explored below, some of Nunavut's apparent risk may be driven by the disproportionate number of Inuit men employed in occupations projected to decline in employment share, as of the 2016 Census (37%).

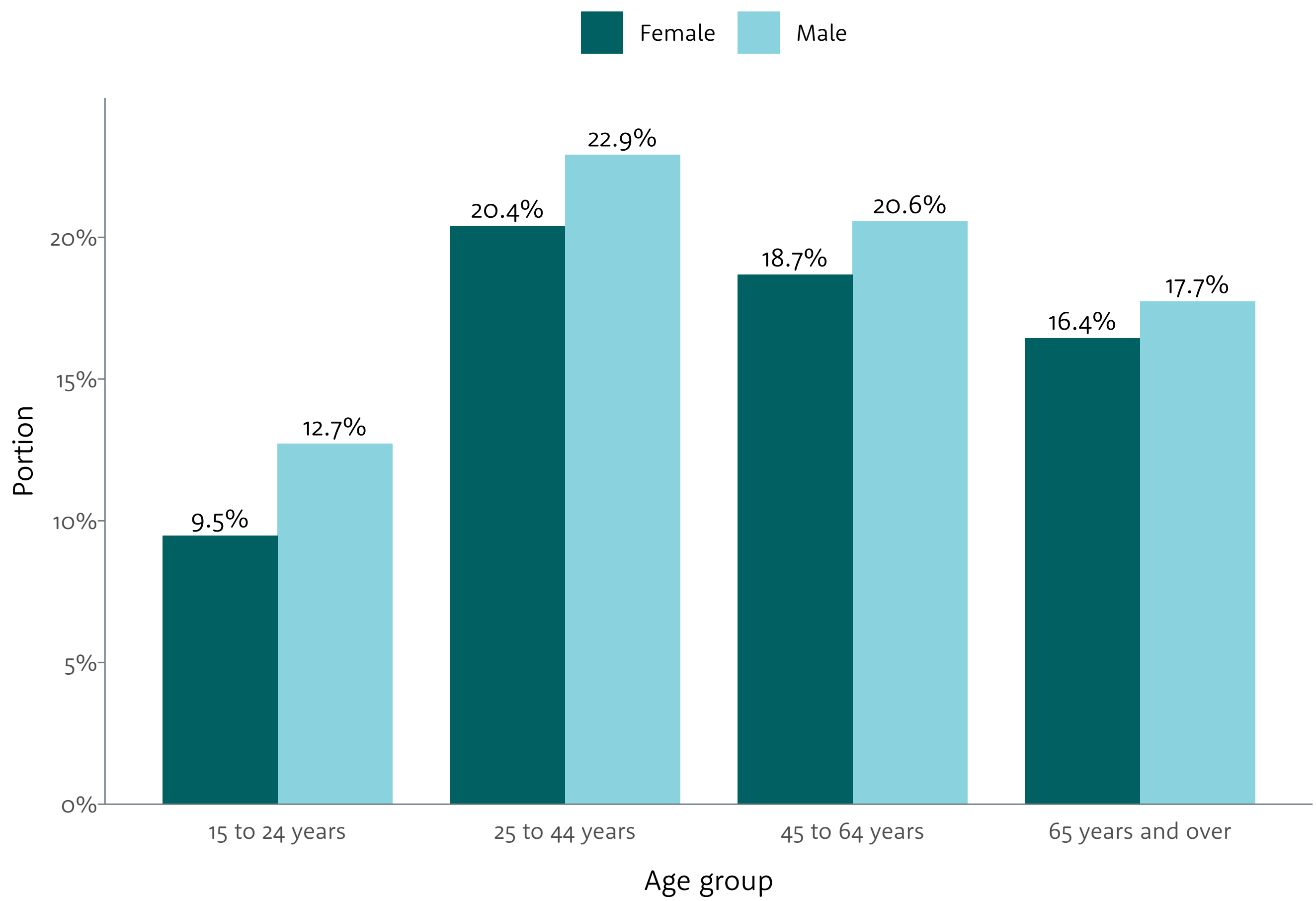
Figure 7: **Regions at a glance**
Workers in occupations projected to decline, by province or territory and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

By age

Figure 8: **Age groups at a glance**
Workers in occupations projected to grow, by age and sex



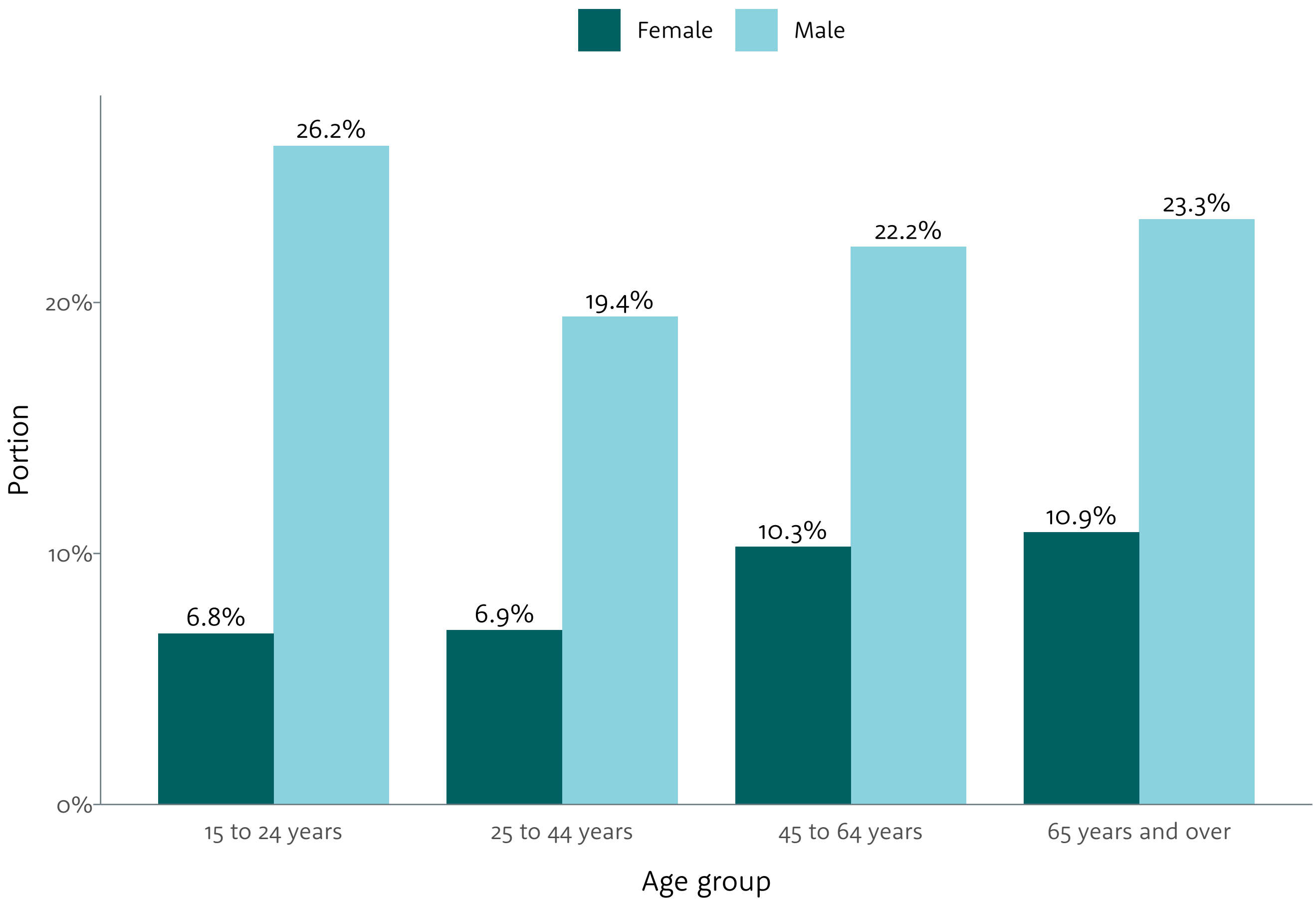
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Opportunities, resilience, and risks

Workers between 25 and 44 years of age are the most likely to hold jobs in occupations with a growth projection. As for the wider workforce, a higher portion of men are in occupations projected to grow *and* in those projected to decline. Women are, at most, half as likely as men to work in declining occupations across all age groups.

The difference between women and men is most marked for the 15-24 age group, particularly for those in occupations potentially declining in employment share. As this age group is also one of the most likely to be in occupations projected to decline, this result warrants a deeper look at the types of jobs that young men and women hold and their prospective career progression. Since these individuals will make up an important part of the workforce in 2030, it is important to identify whether they face significant risk in gaining early and relevant experience for their future. It may be necessary to design initiatives that support their inclusion or advancement into the occupations that experts expect to remain stable or growing.

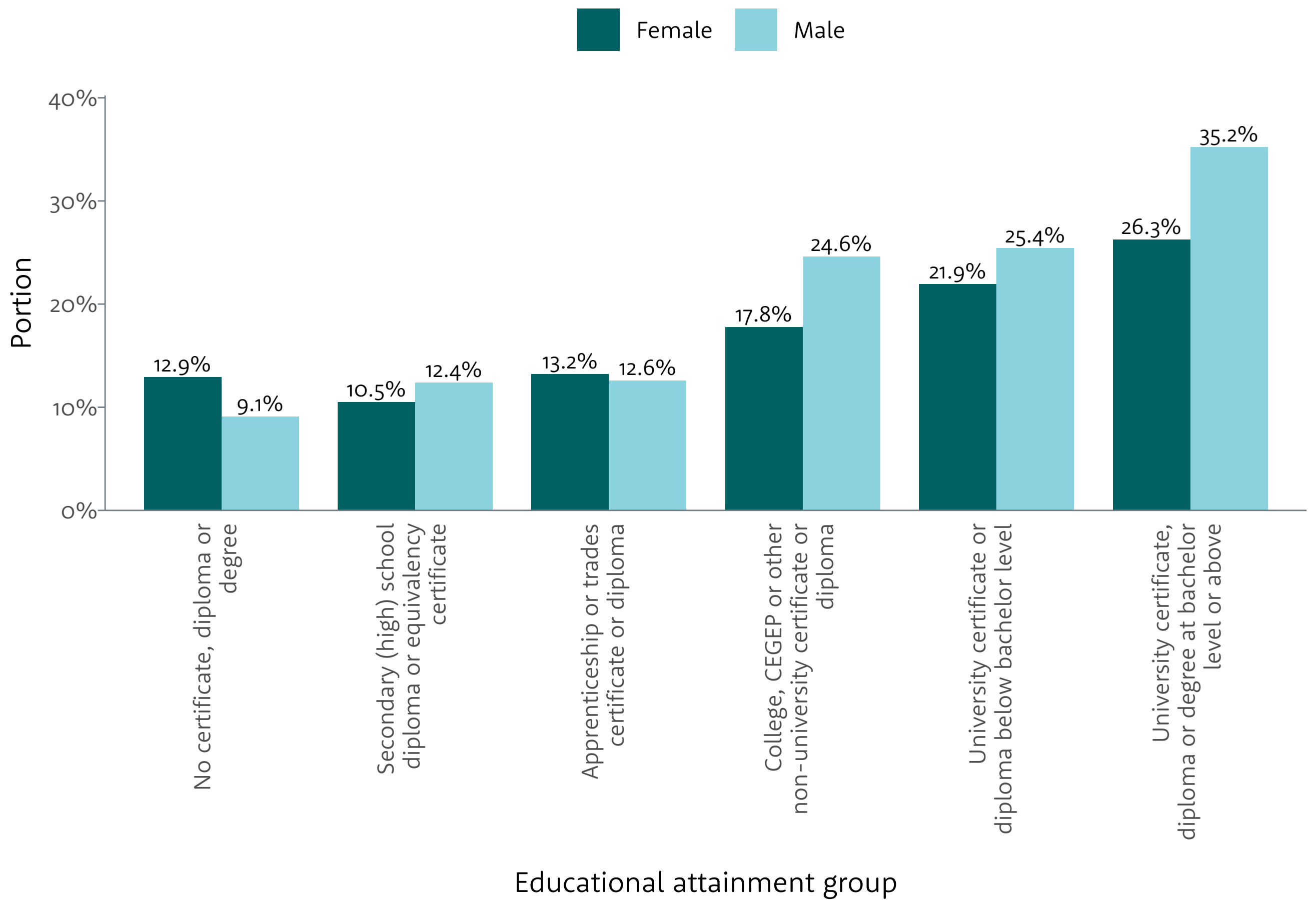
Figure 9: **Age groups at a glance**
Workers in occupations projected to decline, by age and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

By educational attainment

Figure 10: **Educational attainment at a glance**
Workers in occupations projected to grow, by educational attainment and sex



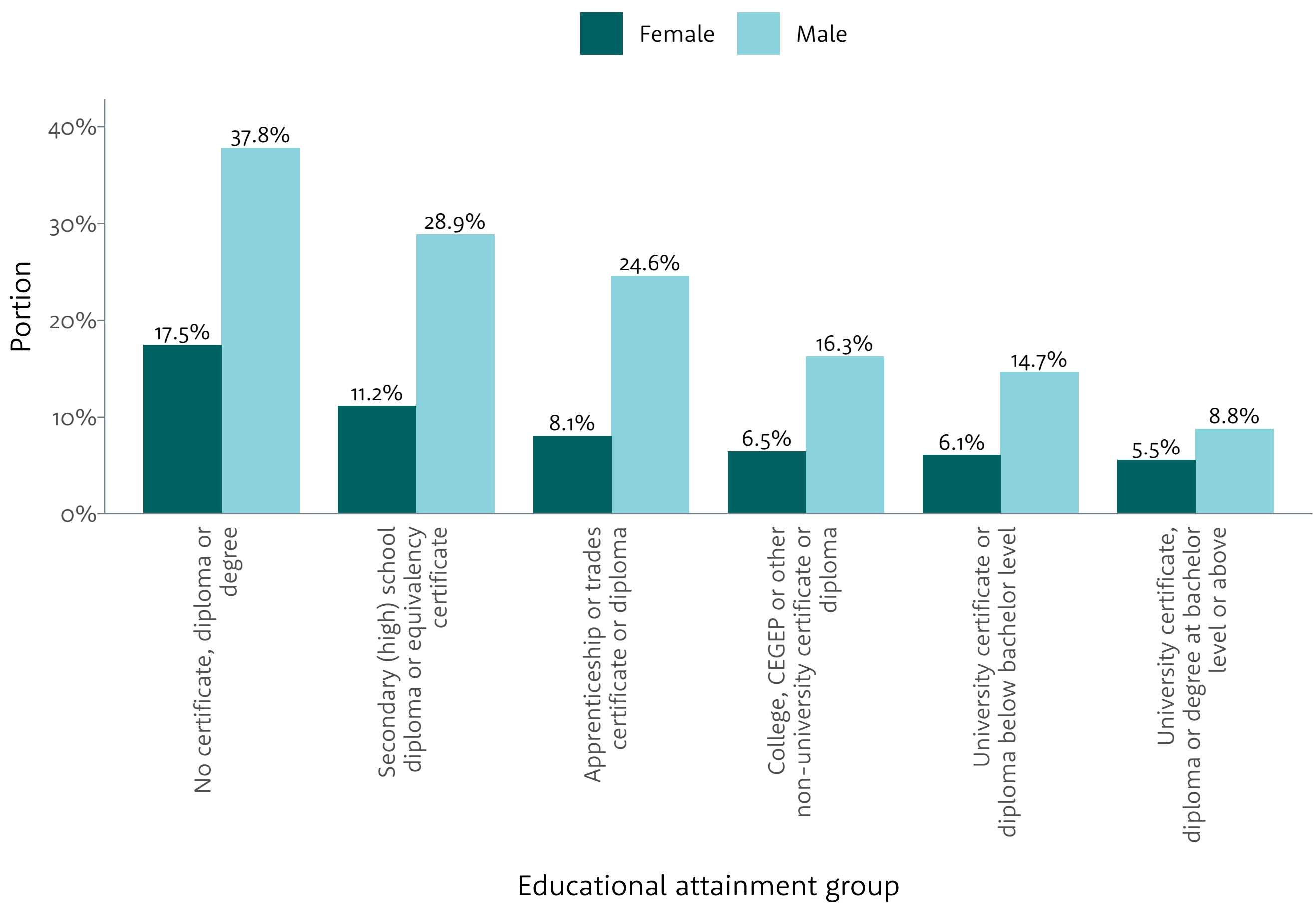
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Opportunities, resilience, and risks

Workers, especially men, holding a bachelor's degree or higher are the most likely to work in an occupation projected to expand. In general, people who have completed CEGEP, a college education, or university certificates are also more likely to work in growing occupations. Men maintain a significant advantage in these attainment categories as well. This result is consistent with recent educational and hiring trends, which track a marked increase in the level of Canadians' educational attainment over the past two decades.[130]

Notably, men with lower educational attainment are also disproportionately represented in occupations projected to decrease. Two in five men without a high school education work in these, compared to one in five women. Across various levels of educational attainment, women are less likely to work in occupations projected to decline in employment share.

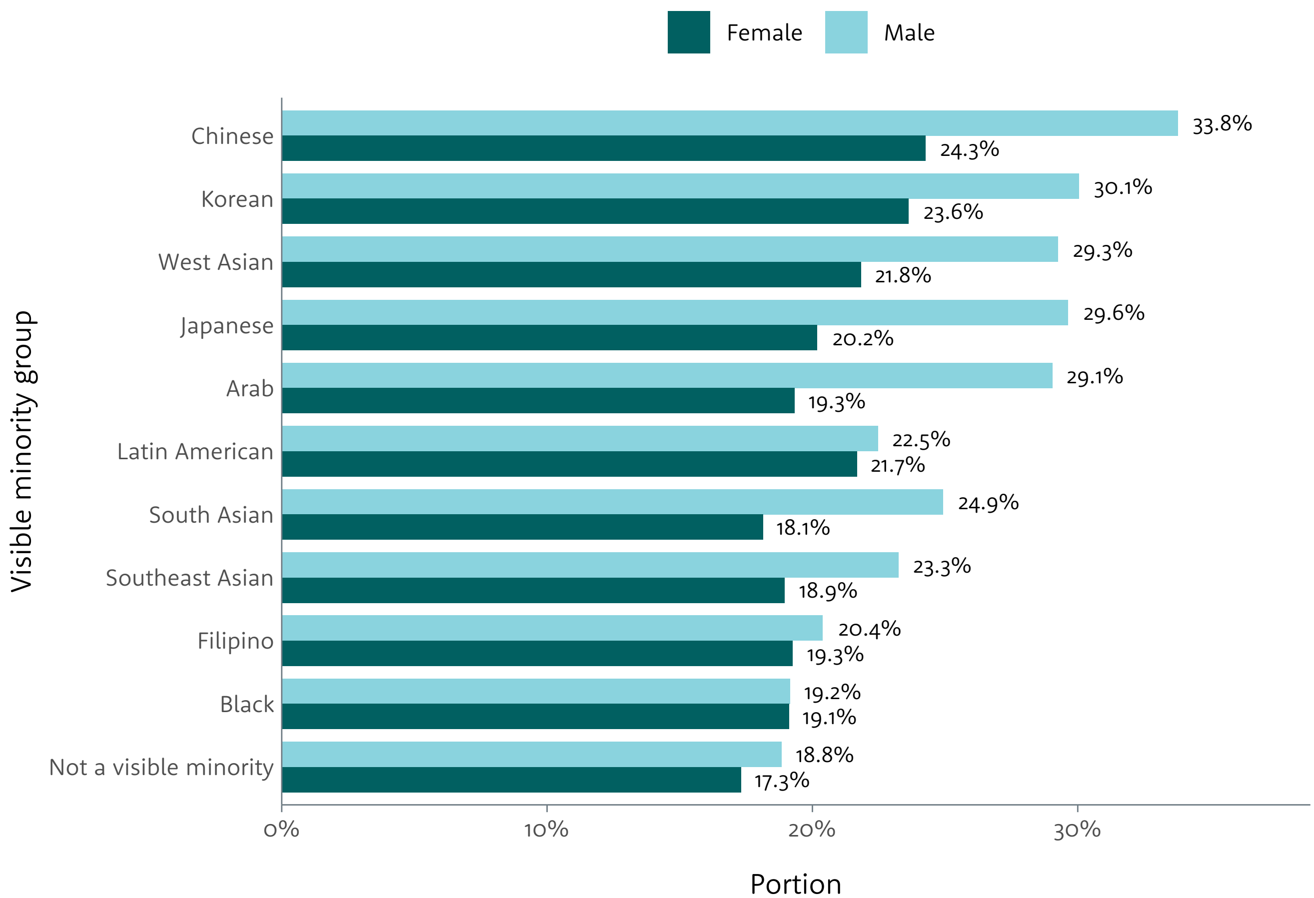
Figure 11: **Educational attainment at a glance**
Workers in occupations projected to decline, by educational attainment and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

By visible minorities

Figure 12: **Visible minorities at a glance**
Workers in occupations projected to grow, by visible minority and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Definition: Visible minority

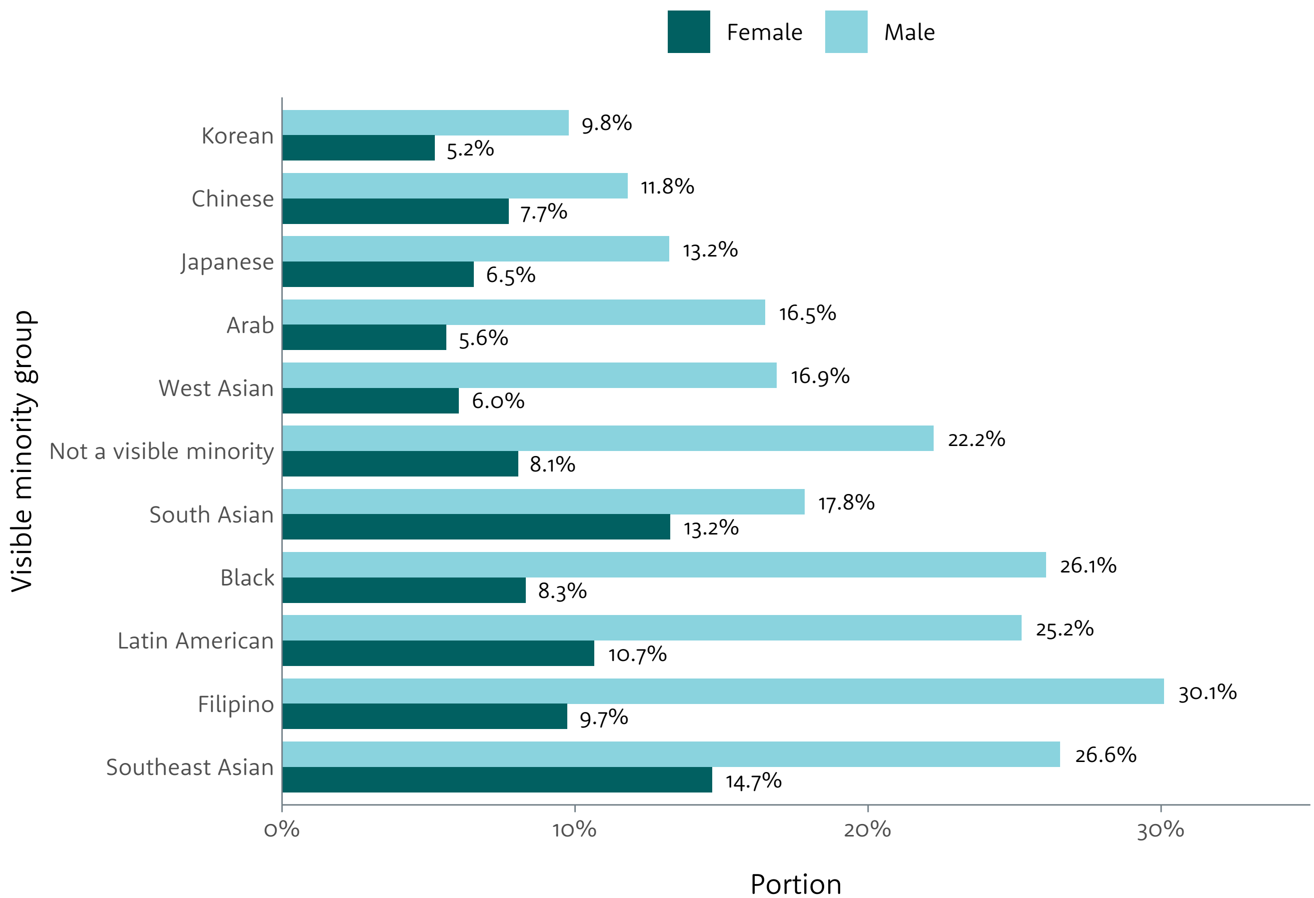
Canadian Census information on visible minorities relies on the definitions set out in the Employment Equity Act. The act defines visible minorities as "persons, other than Aboriginal peoples, who are non-Caucasian in race or non-White in colour". It includes the following categories: South Asian, Chinese, Black, Filipino, Latin American, Arab, Southeast Asian, West Asian, Korean, Japanese, n.i.e. (not included elsewhere), Multiple Visible Minorities, and Not a Visible Minority.

Source: Statistics Canada [131]

Opportunities, resilience, and risks

Making up almost a quarter of the current Canadian workforce, and projected to account for over one-third of workers by 2036, visible minority groups are a growing demographic. On average, they are slightly more likely to be working in occupations that experts project to increase than people without visible minority identities.[132] Overall, women of colour are employed in occupations with less projected change than men, and could therefore experience both fewer opportunities and fewer risks in the future within their current roles.

Figure 13: **Visible minorities at a glance**
Workers in occupations projected to decline, by visible minority and sex



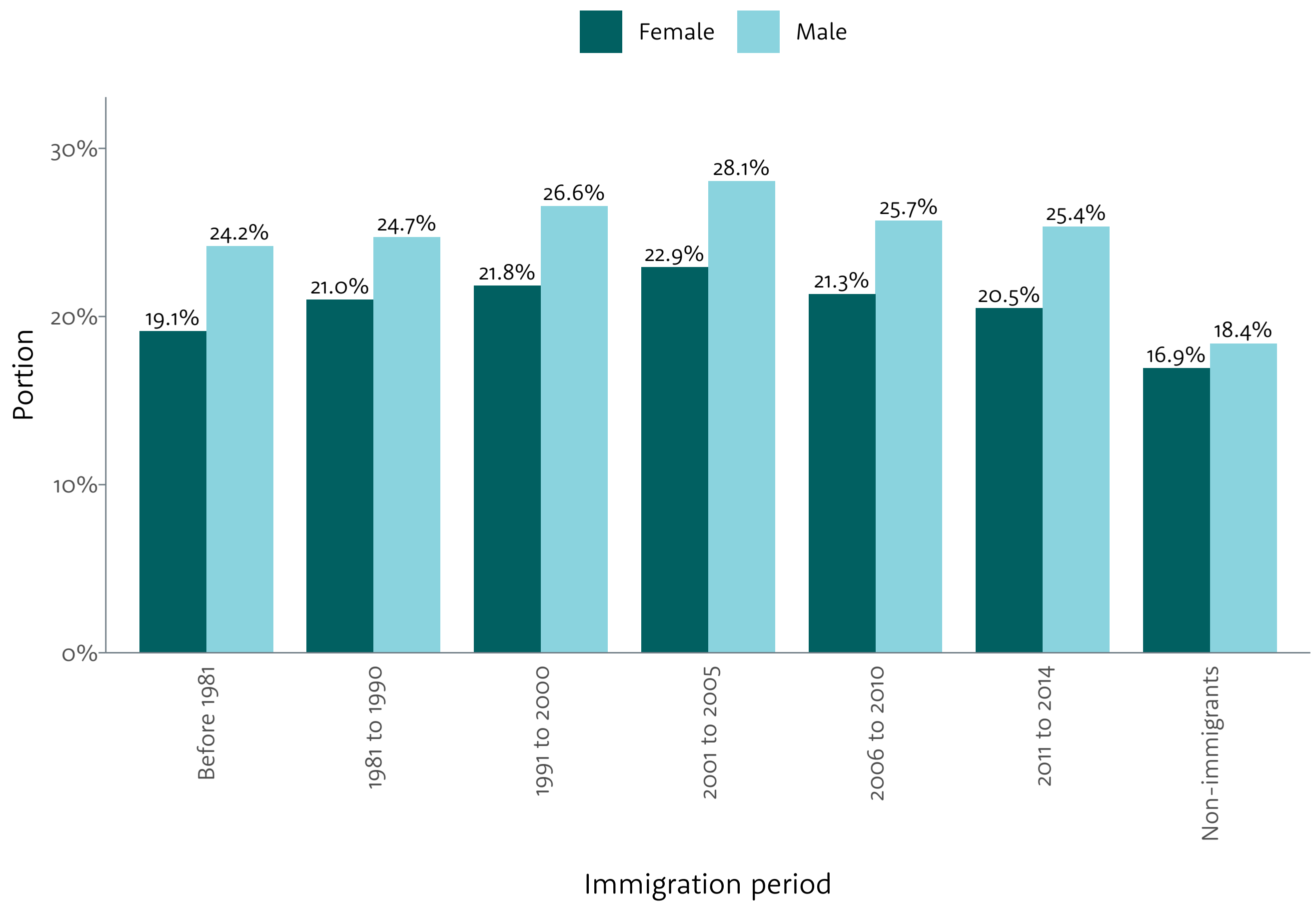
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

In particular, Chinese, Korean, and Japanese men have the highest portion of workers likely to be in occupations that are projected to increase, and are on average eight percentage points more likely to be in an increasing occupation than women with these identities. These visible minority groups are also less likely to be in occupations projected to decrease. This relationship may, however, be partly correlated to educational attainment. Visible minority groups are 12.5 percentage points more likely to have a university certificate, diploma, or degree at the bachelor level or above compared to the general population.[133]

While a fairly high percentage of people with visible minority identities are working in jobs projected to increase, they are also more likely to be in occupations that are projected to decrease. Across visible minority groups, a higher percentage of men are in occupations projected to decline. For example, 30% of Filipino men are in occupations projected to decrease, with Southeast Asian and Black men following closely behind. When looking at participation and pay disparities, previous BII+E work finds similar polarity among different visible minority groups in Canada's tech sector.[134]

By period of immigration

Figure 14: **Immigration at a glance**
Workers in occupations projected to grow, by immigration period and sex



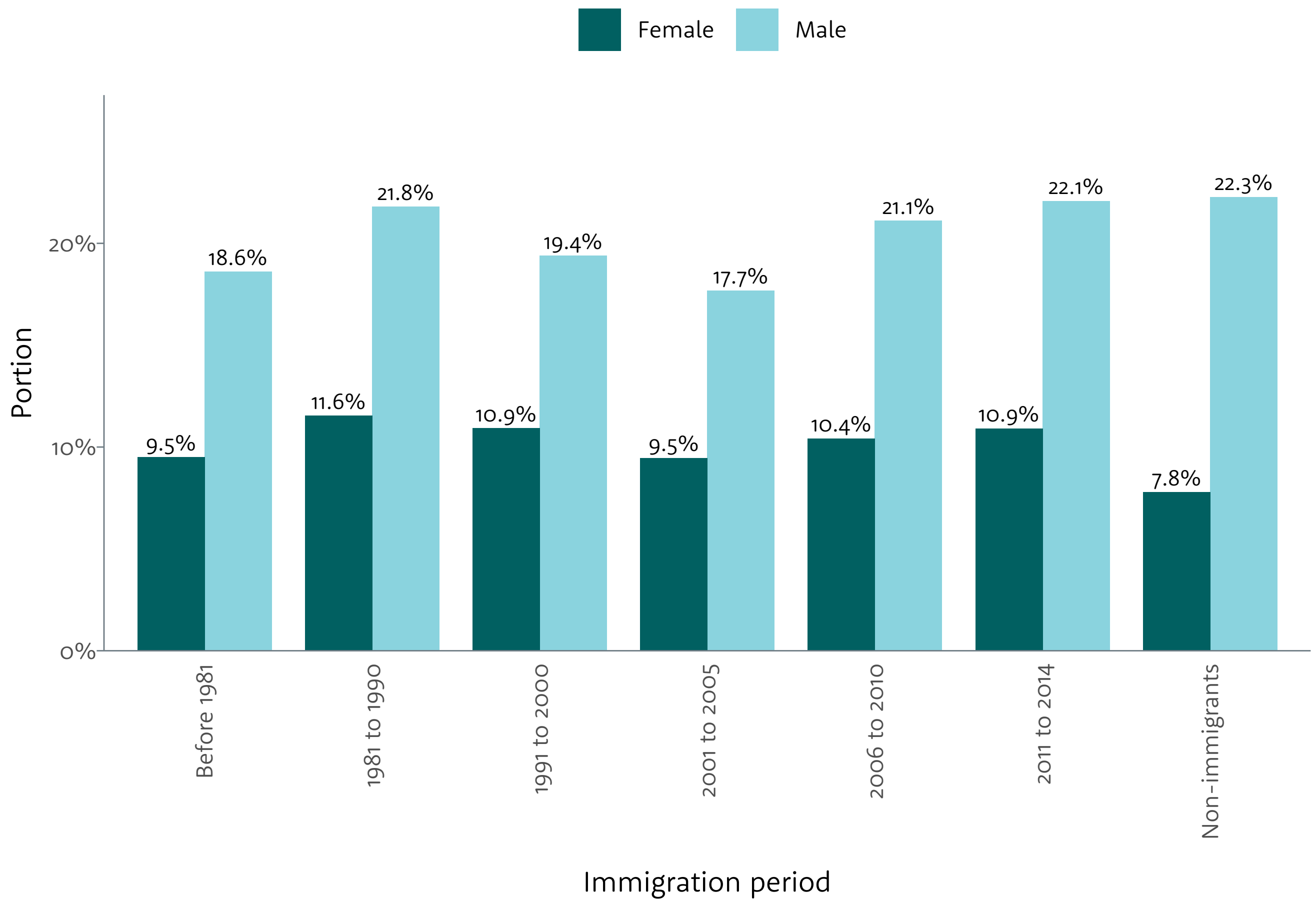
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Opportunities, resilience, and risks

In general, a higher percentage of workers who recently immigrated to Canada are in occupations projected to increase compared to non-immigrants. Immigrants who arrived in the country between 2000 and 2005 have the highest portion in these occupations, at 28%. This higher potential resilience, when compared to the workforce average, may be a reflection of Canadian immigration policy that prioritises economic class admissions. For this class, the immigration system considers factors such as gaps in the labour market, educational attainment, and previous Canadian experience, all of which might increase the likelihood of finding work in an occupation projected to grow.[135] Age, Canadian experience post-arrival, and other factors may also play a role.

Figure 15: **Immigration at a glance**

Workers in occupations projected to decline, by immigration period and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

Women in this group are more likely to be in occupations projected to both increase and decrease in comparison to non-immigrant women. This result suggests they might face both higher opportunity and higher risk in the coming decade. However, there is a larger portion of male immigrants in occupations projected to undergo change (both growth and decline in employment share) than their female counterparts, mirroring the wider workforce.

By Indigenous identity

Indigenous identity

Under the Statistics Canada definition, "Aboriginal identity refers to whether a person identified with the Aboriginal peoples of Canada. This includes those who are First Nations (North American Indian), Métis or Inuk (Inuit) and/or those who are Registered or Treaty Indians (that is, registered under the Indian Act of Canada), and/or those who have membership in a First Nation or Indian band".[136] It is important to note that in data collection, the Census program relies on self-identification from respondents. As with previous BII+E reports, while the dataset informing this analysis uses this definition, this report uses the term Indigenous in line with a broad shift towards a term that better reflects a wide array of Indigenous identities in Canada and globally.[137]

For Indigenous peoples in Canada, data collection, use, and ownership can be a complex and controversial issue. Historically, data collected from Indigenous communities has been used to their detriment, helping to perpetuate inequality and discrimination.[138] Due to this historical context, many Indigenous communities and individuals have refused Census enumeration by the government of Canada, leading to incomplete data in the Census.[139] While Indigenous groups' participation in the Census has increased over the past two decades, 14 communities were incompletely enumerated in 2016 and not captured in this data.[140]

BII+E's stakeholder consultations also revealed that the NOC structure and the O*NET taxonomy do not appropriately capture the occupations and skills of many Indigenous peoples. These factors may have resulted in important omissions from the data presented in this report, introducing additional error to its extrapolations.

Organisations like the First Nations Information Governance Centre aim to address these gaps through new collaborative tools that ensure the data and its benefits belong to First Nations communities, including the First Nations Regional Early Childhood, Education, and Employment Survey. Their national report accompanying the second iteration of the survey is scheduled for release in 2021.[141]

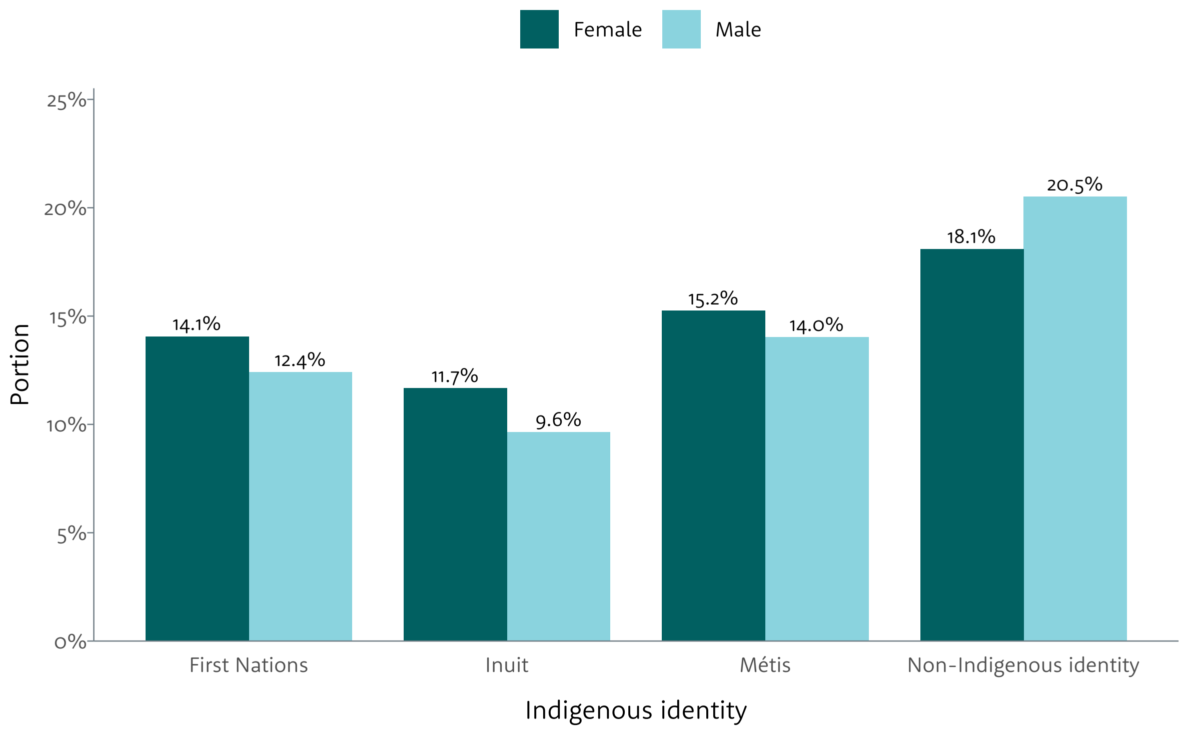
Opportunities, resilience, and risks

Contrary to the trend seen in other demographic groups, Indigenous women are more likely to be in occupations that are projected to increase in employment share than Indigenous men. However, the proportion of Indigenous individuals who are in these occupations remains significantly lower than that of non-Indigenous people. This portion is 15%, less than both people who do not identify as visible minorities (20%) and visible minority groups (25%).

Indigenous workers are much more likely to work in occupations projected to decrease than occupations projected to increase. The lower average number of formal educational credentials and secondary school graduation rates recorded for Indigenous peoples may partly drive these results, given the relationship seen in the Educational Attainment section of this analysis.[142] [143]

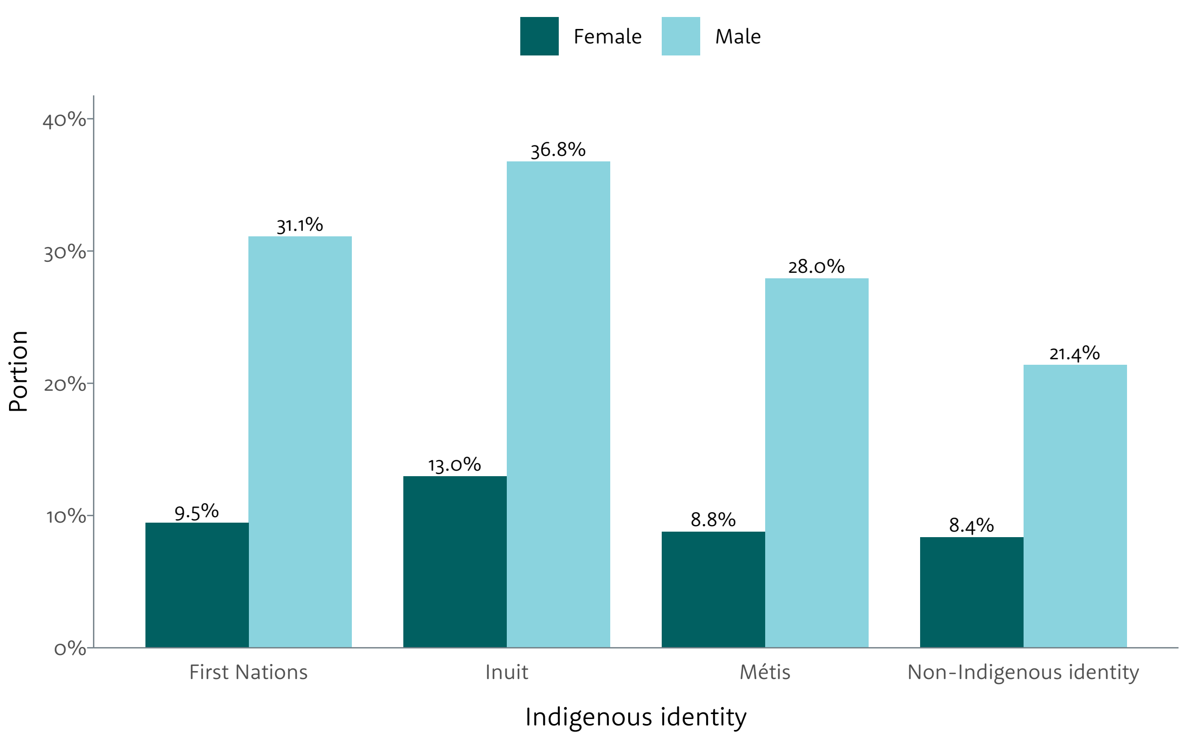
In particular, Indigenous men are disproportionately represented in occupations projected to decrease when compared to non-Indigenous people. The data suggests that Inuit men may be exposed to the most risk due to labour market change, with 37% working in occupations projected to decrease. However, it is important to note that the indicators in the 2016 Census as well as this forecast lack comprehensive consideration of the cultural, historical, and environmental realities of Indigenous peoples. As a result, they could be inappropriately applied to the

Figure 16: **Indigenous peoples at a glance**
Workers in occupations projected to grow, by Indigenous identity and sex



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

Figure 17: **Indigenous peoples at a glance**
Workers in occupations projected to decline, by Indigenous identity and sex



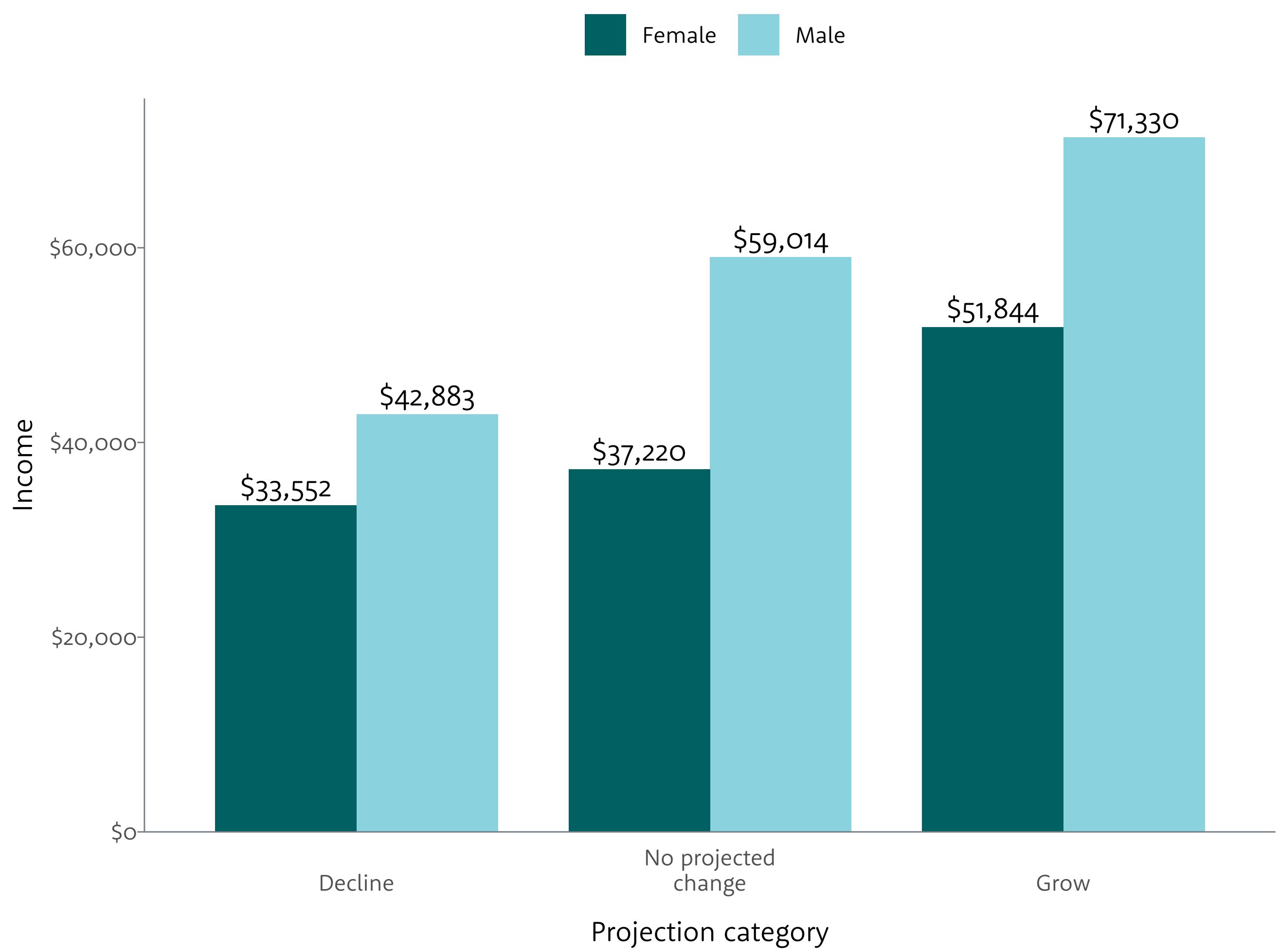
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

Indigenous context and be used to draw harmful and invalid conclusions.[144] Important nuances lie with regional and cultural elements, which warrants further exploration.

By income

Figure 18: **Income at a glance**

Average income of workers in occupations projected to grow, decline, or remain stable

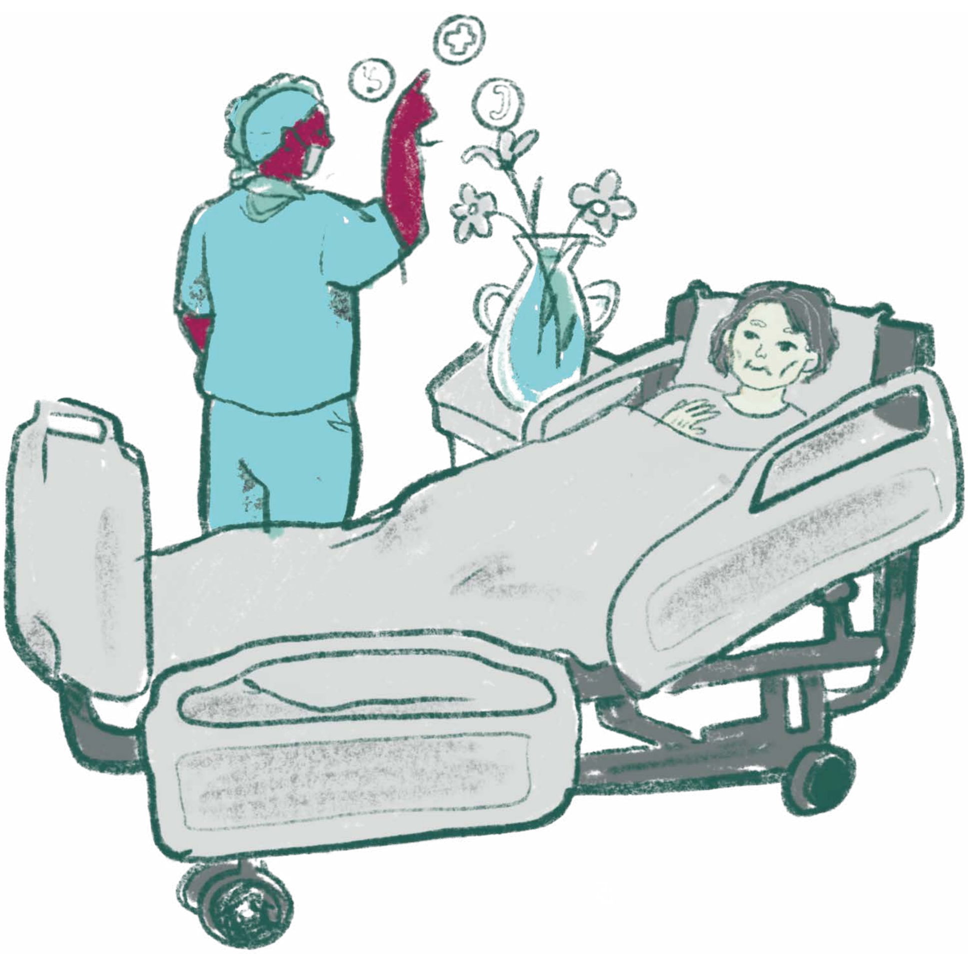


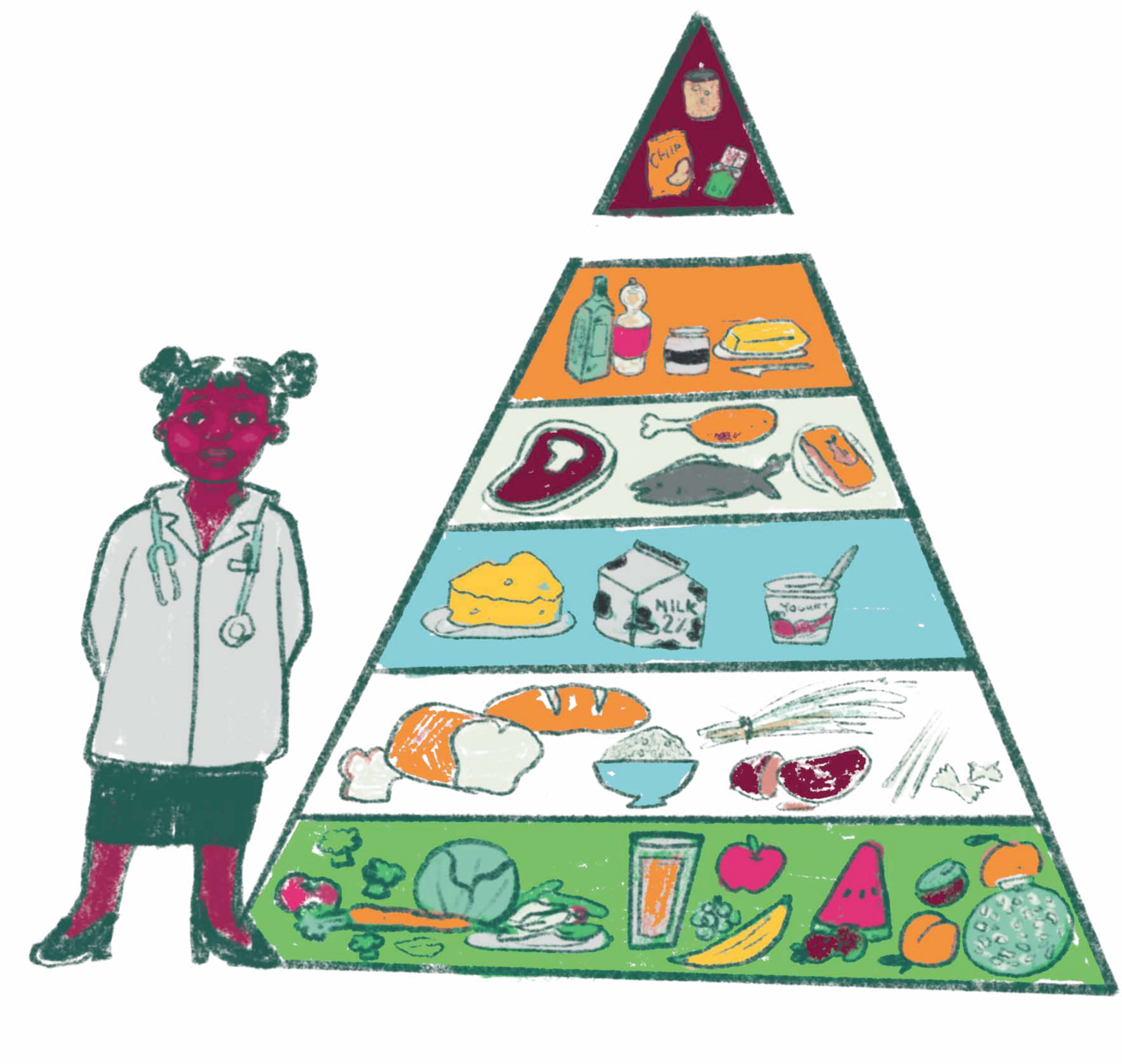
Sources: 2016 Canadian Census, BII+E Analysis

Opportunities, resilience, and risks

Those in occupations projected to grow made more, on average, than those in occupations with no projected change. They, in turn, earned more than those in occupations projected to decline in employment share as of the 2016 Census. In each group, women have a lower average salary than men, and the difference is particularly prominent for those in an occupation projected to grow or remain stable. An alternative look at the income data reveals that 57% of women who work in occupations with an average employment income that exceeds $60,168 and falls in the fourth income quartile, are in occupations projected to grow. In comparison, only 36% of men in occupations where their average employment income is in the fourth quartile work in these jobs.

In general, workers in occupations with an average compensation exceeding $60,168 are over twice as likely to be employed in occupations projected to grow as those in lower income quartiles.[145] This result may point to barriers encountered by those with lower incomes which may affect both incumbent and new workers entering the market over the next decade. In particular, while women are less likely to be in jobs projected to decline, those who do work in these occupations earn significantly less than men ($33,551 versus $42,883), potentially increasing their vulnerability. Further study on the relationship between income and growth projections may highlight additional areas in need of action.





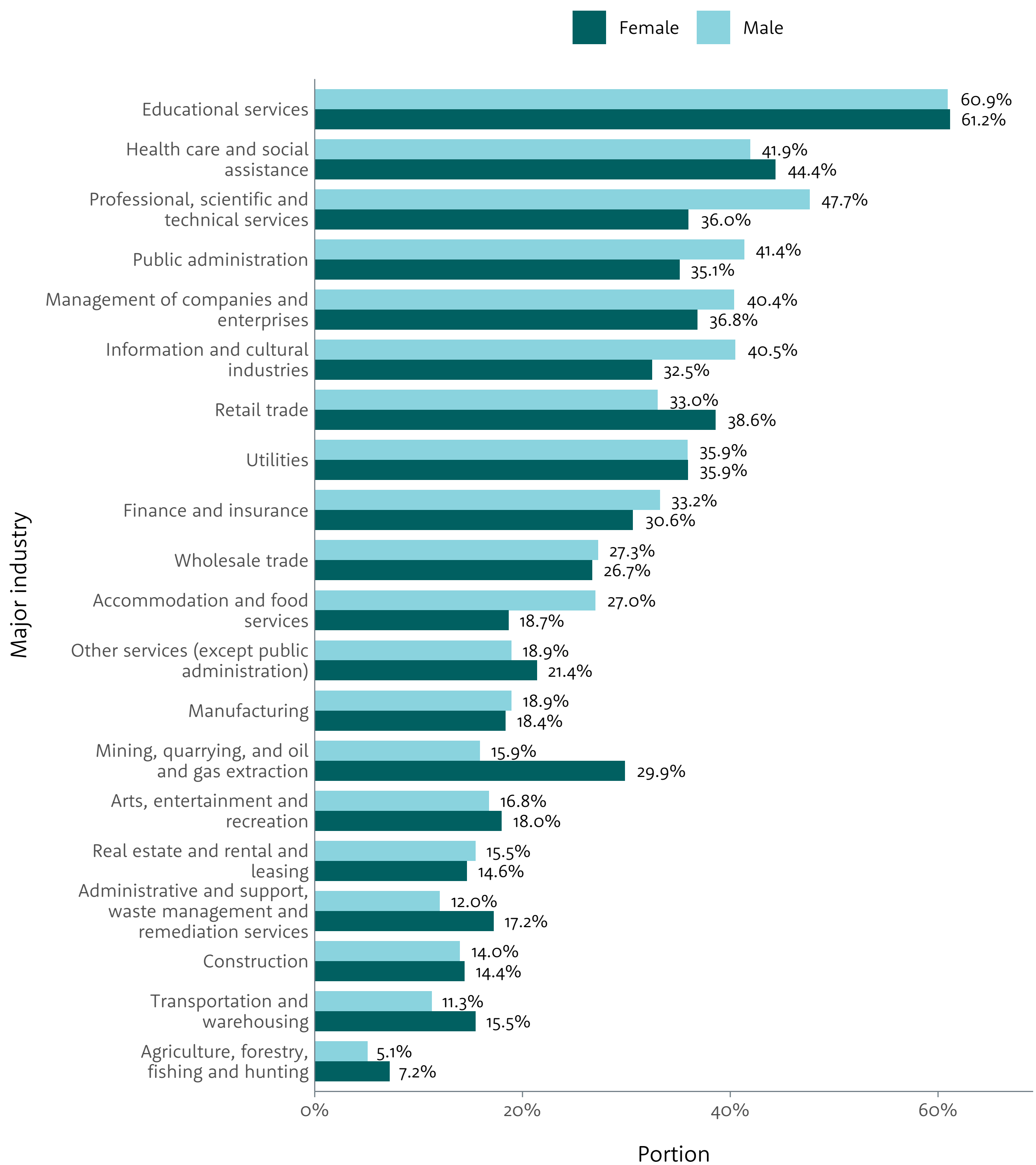
WHO HAS THE 5 FOUNDATIONAL SKILLS?

By industry

When considering the distribution of workers likely to hold all foundational skills across major industry groups (based on their current occupations), it becomes evident that most top performing industries are also those with the highest proportions of employees in occupations projected to grow in this forecast. The converse is also true: the industries that employ the lowest portion of people in occupations that require the five foundational attributes have a fairly high portion of workers in jobs projected to decline in employment share.

There are three notable exceptions. Although the majority of those working in educational services are in occupations that require all of the foundational traits, only 20% of all people in this industry are in occupations projected to grow. This illustrates that while foundational skills and abilities increase the likelihood that experts would rate an occupation as growing in employment share, they are not sufficient to guarantee this projection. The sector dealing with the management of companies and enterprises sees a similar situation. While 38% of workers in this industry are in occupations that require the foundational attributes, only 25% are in occupations projected to increase. On the other hand, those working in occupations in the administrative and support, waste management and remedial services sectors have a relatively low portion of workers in occupations that both require foundational skills and are projected to decrease. These occupations may be less likely to experience change in the labour market despite the lower relative importance of the five foundational attributes.

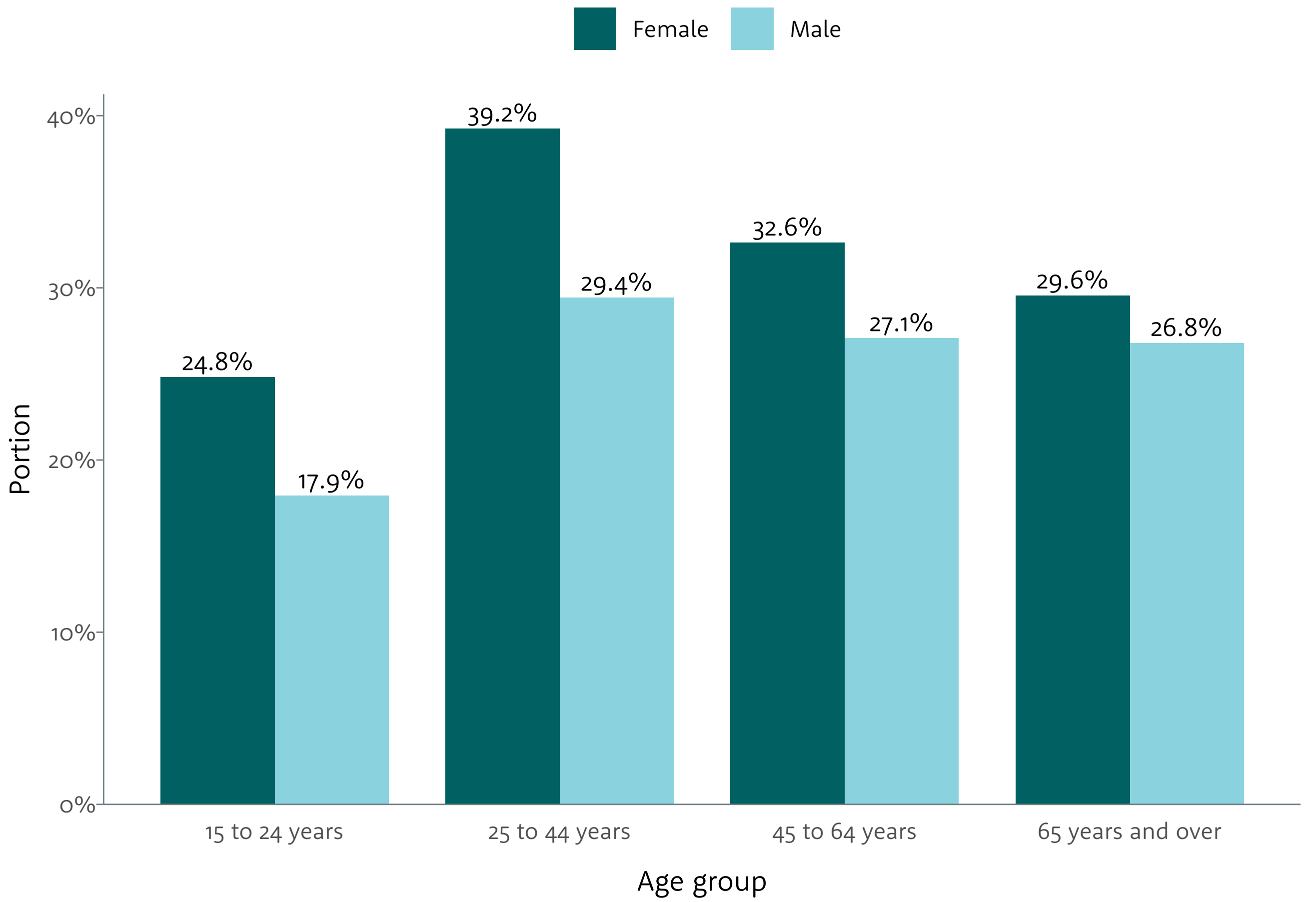
Figure 19: **Foundational traits**
Workers in occupations with all foundational traits, by industry



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

By age

Figure 20: **Foundational traits**
Workers in occupations with all foundational traits, by age

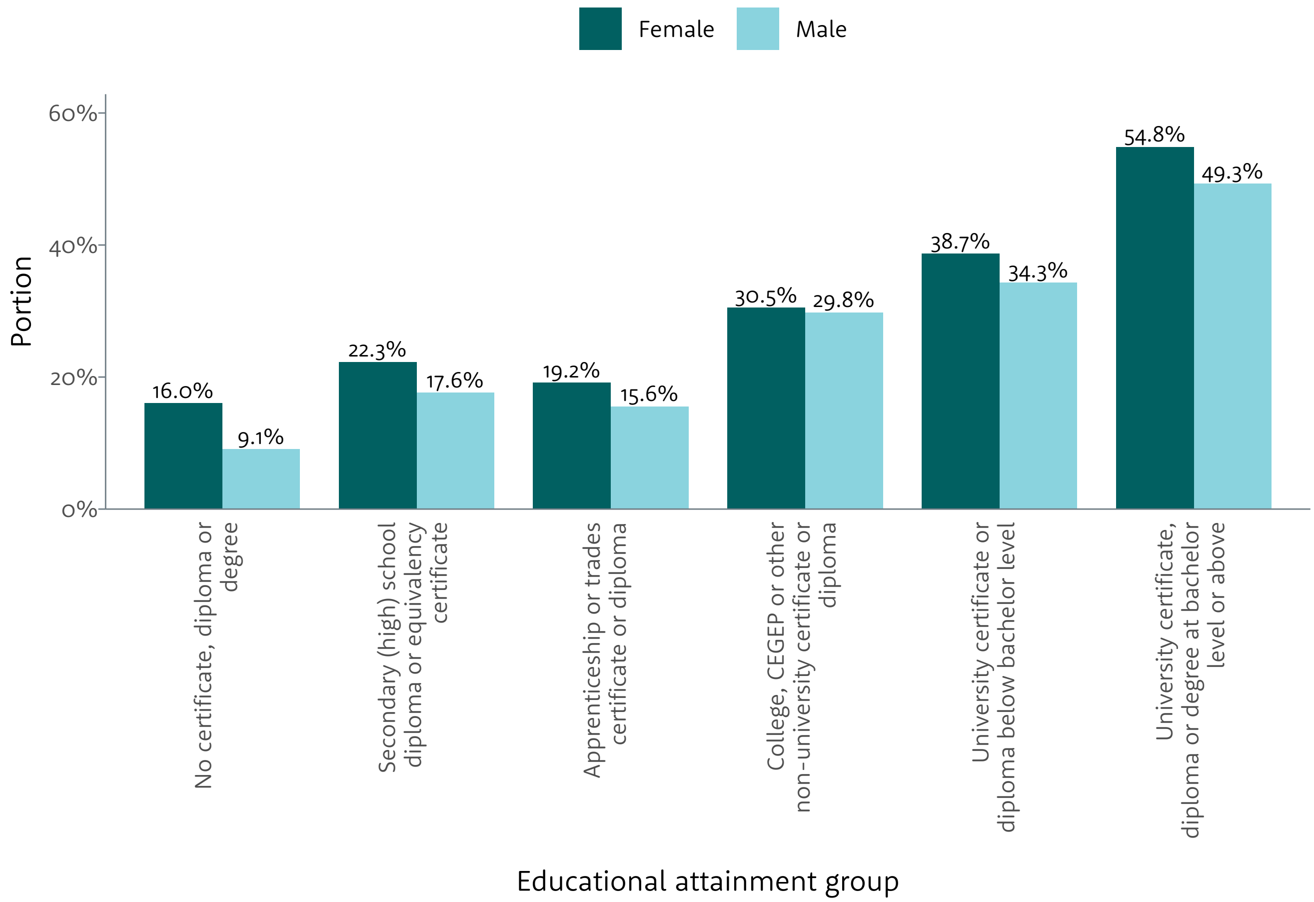


Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

There is a similar age breakdown in the proportion of workers in occupations that require the five foundational skills and the portion of those who are in occupations projected to increase. Workers aged 25-44 are the group most likely to work in both. Notably, despite being less represented in jobs projected to grow compared to men, more women have jobs that need all five foundational skills and abilities than men. For those 25 to 44 years of age, the share of women who work in such occupations is 9.8 percentage points higher.

By educational attainment

Figure 21: **Foundational traits**
Workers in occupations with all foundational traits, by educational attainment

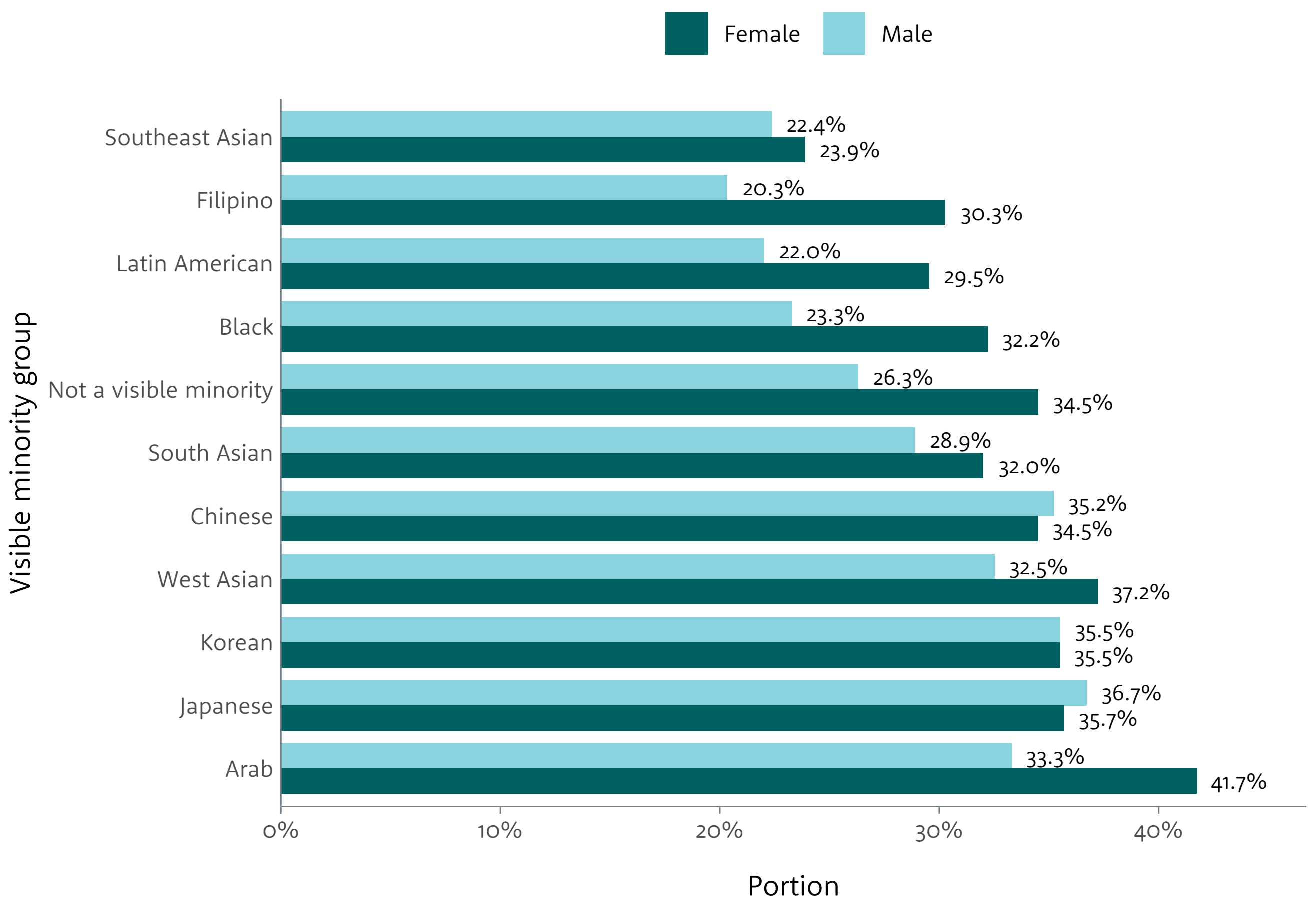


Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a growing occupation.

About half of all workers with university degrees hold jobs in occupations where the five foundational skills and abilities are required. Across educational categories, people with all foundational traits are almost equally likely to be of either sex, although women are slightly more represented in this group. In particular, workers without a high school diploma or its equivalent, as well as those who have completed an apprenticeship, are the least likely to be in an occupation for which all five—memorization, fluency of ideas, instructing, persuasion, and service orientation—are necessary. In the case of the trades, which tend to be very specialised, this result does not necessarily indicate risk. However, individuals without a high school diploma and those with no formal educational credentials in addition to a high school degree may experience lower resilience to potential changes in the labour market.

By visible minority

Figure 22: **Foundational traits**
Workers in occupations with all foundational traits, by visible minority



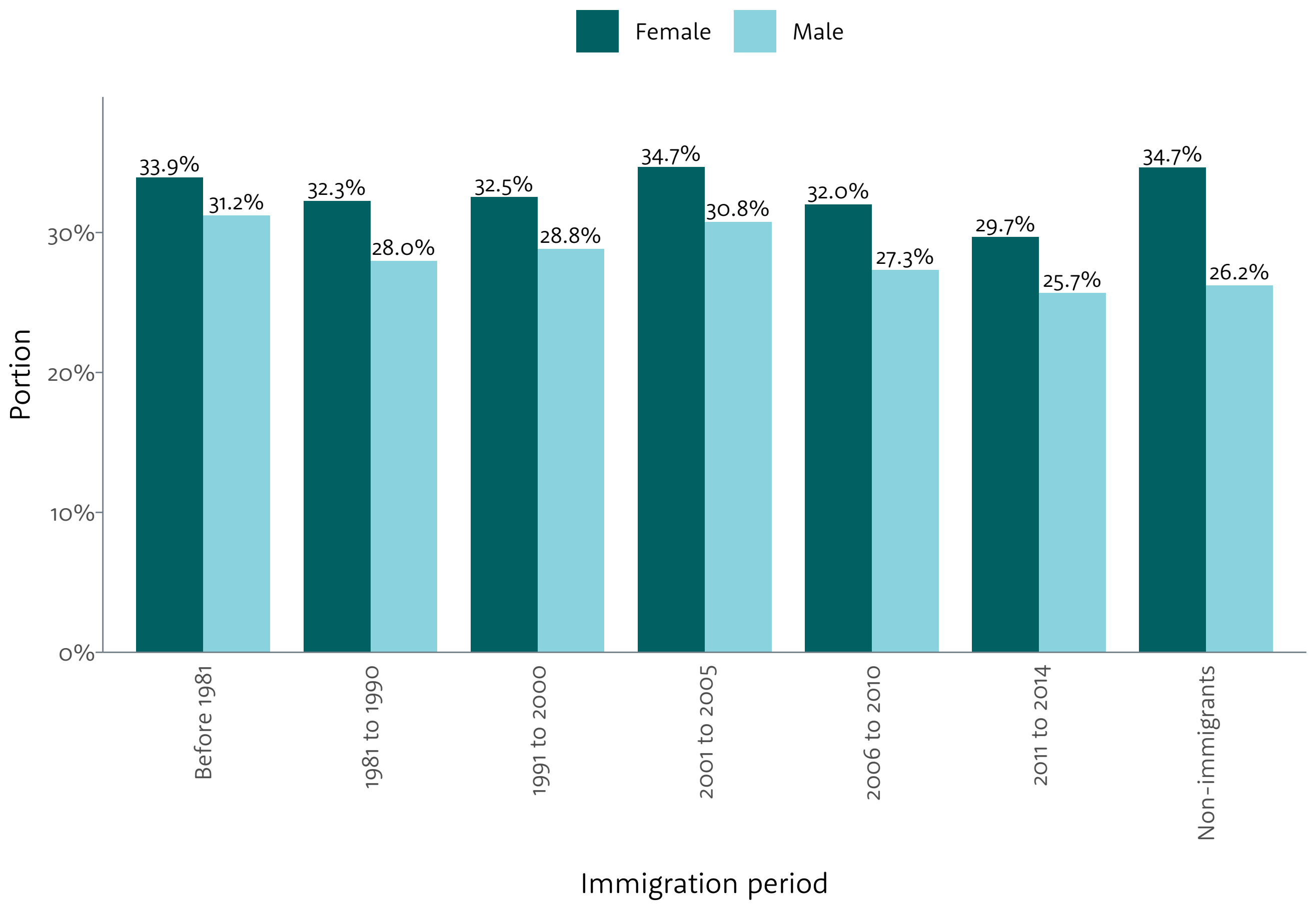
Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

The visible minority group with the highest portion of workers in an occupation that requires all the foundational traits is Arab men and women at approximately 37%. They are followed closely by Japanese and Korean groups, at 36 and 35% of workers respectively. Notably, the five visible minority groups with the highest portion of workers in occupations projected to increase also have the highest portion of workers with all foundational traits. The demographic group with the highest portion of people working in an occupation that currently requires all foundational skills and abilities is Arab Women at 42%. Overall, more women within visible minority groups hold a job likely to need the five foundational traits than their male counterparts.

Workers with Southeast Asian, Filipino, Latin American, and Black identities are least likely to be in occupations requiring foundational skills. Given that they are also the most likely to be in occupations projected to decline in employment share, this result indicates a higher potential exposure to labour market changes in the coming decade.

By immigration

Figure 23: **Foundational traits**
Workers in occupations with all foundational traits, by immigration period

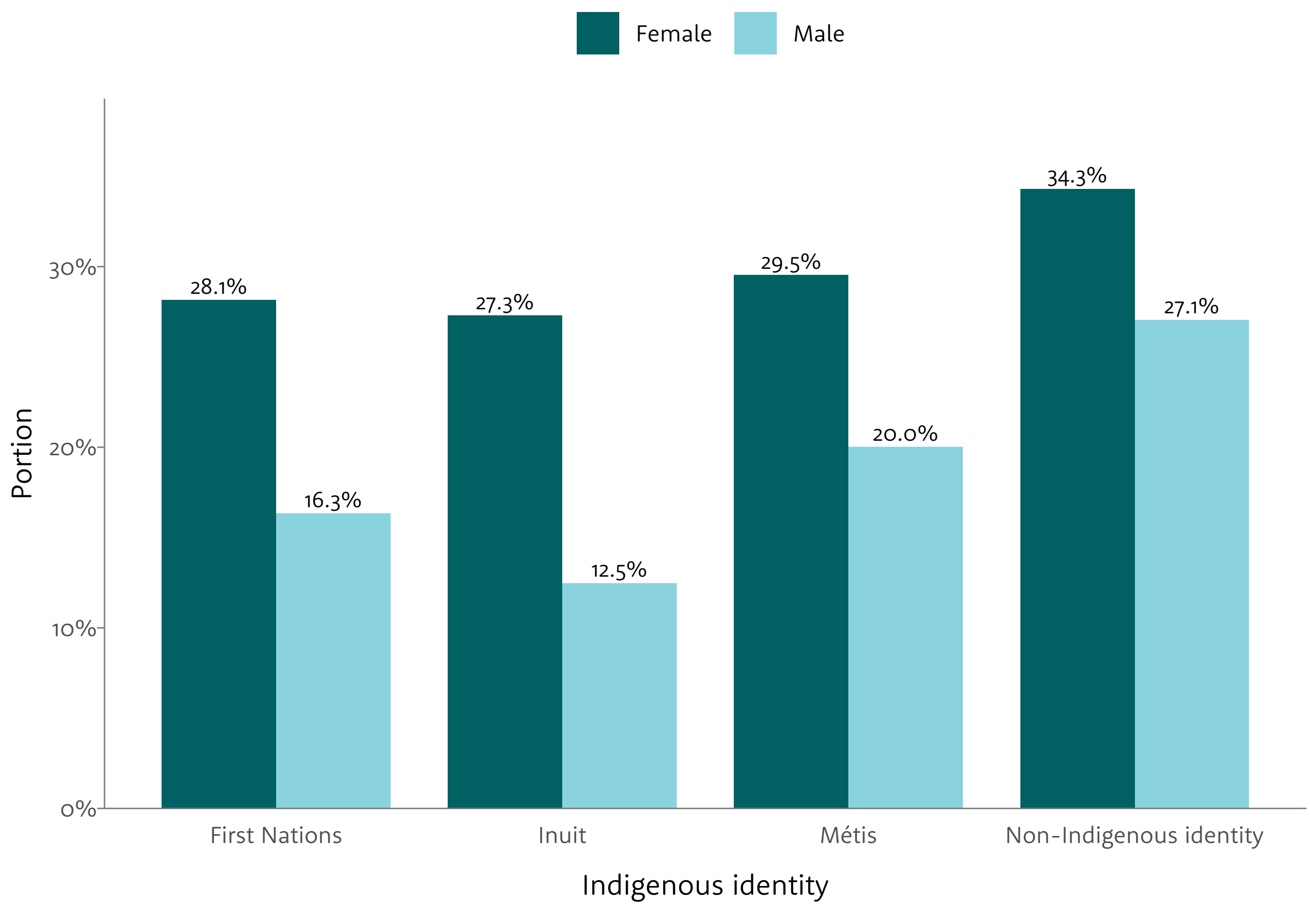


Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

First-generation immigrants and non-immigrant workers have comparable levels of foundational skills and abilities. Notably, the highest groups of workers in jobs requiring these traits either immigrated to Canada between 2001 to 2005 or were born in the country. Similarly to other demographic groups, more female immigrants tend to work in occupations that need the foundational skills than their male counterparts.

By Indigenous identity

Figure 24: **Foundational traits**
Workers in occupations with all foundational traits, by Indigenous identity



Sources: 2016 Canadian Census, BII+E Analysis
Note 1: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.
Note 2: Each bar represents the portion of a demographic group that is in a declining occupation.

In general, women are in a fairly resilient position regarding foundational skills and abilities, including Indigenous women. Just under one in three employed Indigenous women work in occupations where these traits are required. While a higher portion of non-Indigenous women work in occupations that require the foundational skills, the average difference is slight at 6 percentage points with a maximum difference of 7 points in the case of Inuit women.

However, the average disparity for Indigenous men, when compared with their non-Indigenous counterparts is higher at 9 percentage points, and reaches 14.6 in the case of Inuit male workers.

POLICY INSIGHTS

What do these projections mean for our country and the world in 2030? The decisions that policymakers, educators, and employers make regarding skill and employment investments now will define the labour market in the next decade. This analysis highlights three main areas for action: building skills and unlocking access to education, recognizing the varying needs and realities of different workers, and building the labour market information capacity necessary to track and prepare for possible changes.

SKILLS + EDUCATION FOR THE FUTURE

Integrating the five foundational skills and abilities into education, training, and evaluation programs will help workers remain resilient as the labour market evolves over the next decade.

Fluency of ideas, memorization, service orientation, instructing, and persuasion emerged as necessary traits for most workers both now and over the next decade. Canadian educators, organisations involved in training, and policymakers should consider how these five fundamental attributes are currently taught and evaluated, identify leading best practices, and consider embedding them more widely in existing curricula. These skills are likely to be in demand across the labour market, and their integration into K-12 and postsecondary education, mid-career retraining, and other upskilling courses outside the formal education system may be meaningful in making future workers more resilient.[146]

The foundational traits could also inform official skills assessment, funding, and measurement frameworks, in order to incentivize program-delivery institutions to adopt them into their curricula. ESDC's Essential Skills is a prime example, and the inclusion of the foundational traits would be in line with the ongoing restructuring of the classification, which seeks to add an increased focus on social and emotional skills.

Additional to fundamental skills and abilities, the augmenting and complementary traits identified by this analysis could be useful in more specific contexts. Educators may want to consider opportunities to build these skills into specific fields of study, expanding on students' existing knowledge and their current or prospective fields of work, to boost their ability to navigate and compete in a changing labour market.

Future workers may need support in higher education to unlock opportunity and resilience.

Occupations that are projected to increase in this forecast are also ones that require a high level of education. To ensure that a larger share of workers can access these growing jobs, potential policy responses could include a reduction of barriers, such as those caused by student debt, for individuals to access education beyond high school—including at the college and university levels—or a push toward the recognition of alternative qualifications and micro-credentials by employers. [147]

Workers in different age groups may also need different forms of support. While young workers are the most likely to work in occupations projected to decline, age may also affect willingness to engage in or access to retraining, particularly where short, flexible training options are not available, making older workers more vulnerable.[148]

DIFFERENT WORKERS, DIFFERENT REALITIES

Policies must be designed to be resilient and work not just now, but in different possible futures, in order to minimize the negative consequences of labour market change for Canadians.

This forecast points to industries and demographic areas where potential shifts in employment may warrant proactive support for worker job transitions and highlights skills that are likely to be valuable across the economy into the future. Acting on these insights now could help steer us towards a more desirable future, one in which workers are equipped to adjust to change and find well-paying jobs and employers are able to readily source needed talent. Realizing this future may require new partnerships between employers, education institutions, governments and unions, and new solutions.[149] [150] Laying the groundwork early will be key, as 34% of workers are currently in an occupation projected to change. Both workers and employers will need support in navigating these shifts.

Special attention may be needed to develop workforce adjustment strategies for workers and employers within industries and regions projected to experience a high level of change.

In some cases, efforts are already underway to help workers transition from areas of decline to areas of growth, as employers, governments, unions, and others are responding. In other cases, proactive development of partnerships and potential job pathways still need to be recognized as necessary ways to help to make these transitions smoother. In particular, while many industries are set to be fairly resilient, four major industries have more than 25% of workers in jobs projected to decrease: agriculture, forestry, fishing, and hunting; manufacturing; mining, quarrying, and oil and gas extraction; and construction. On the regional front, workers in Nunavut, Saskatchewan, and the Northwest Territories are not only less likely to be in the occupations that experts project will increase; they also have a much higher likelihood of being in declining occupations than workers from other regions.

Targeted investments that recognize the different risks and opportunities faced by men and women, as well as workers from different demographic groups, would help even out disparities, promoting greater equity in the future.

Female workers are less likely to be in occupations projected to grow, but also less than half as likely as their male counterparts to be in occupations projected to decline. However, those who do work in jobs projected to decline in employment share make significantly less than men ($33,551 versus $42,883), potentially increasing their vulnerability. This may point to a need for initiatives that support women in gaining access to higher pay and employment in occupations projected to grow.

Men are more likely to work in both occupations projected to grow and those projected to decline in share. In fact, almost 42% of men are in an occupation that is projected to change by 2030, either growing or declining within that time. There are important differences, however, for male workers from different demographic groups. Men from Chinese, Korean, and Japanese descent are more likely to work in an occupation projected to grow, while over 25% of Filipino, Southeast Asian, Black, or Latin American workers hold jobs in occupations projected to decline. These groups are also some of the fastest growing populations in Canada. As a result, there is particular urgency around the need to identify and develop more effective interventions to support a talent pipeline into stable or growing occupations for men from these groups.[151]

Workers in occupations projected to decline earn less than those in occupations projected to increase, making it harder for them to navigate job disruption and compounding the risks they may face. In general, people with lower education and lower incomes are in more precarious positions in a changing economy.[152] This points to a need for job transition and other supports designed specifically to meet the needs of people facing income-related barriers to resilience.

There is a large gap in labour market information available for Indigenous peoples, making it difficult to pinpoint areas for policy focus.

Investments in this area are needed to better enable Indigenous communities to respond to labour market change. These investments should support Indigenous-led initiatives and solutions such as labour market information tools, skills classifications, employment programs, and partnerships that are grounded in Indigenous cultures, languages, contexts, needs, and aspirations.[153] While limited, the available data suggests that among all workers, Indigenous peoples are some of the most likely to be employed in occupations projected to decrease, and least likely to be in growing occupations. Support for Indigenous-led institutions and programs could facilitate increased participation of Indigenous workers in occupations projected to grow, and help minimize gaps in educational and economic outcomes.[154] [155]

There will be a continued need for investments in programs that help immigrants transition into jobs where demand is projected to grow.

Workers who have immigrated to Canada are more likely to be employed in growing occupations. This is true for both women and men, and may be correlated with the higher average level of formal educational attainment of immigrant populations.

As immigration continues to be a main driver of workforce and population growth in Canada in the next decade, it will be important to ensure that opportunities are available and accessible for newcomers.[156]

BUILDING RESILIENCE THROUGH INFORMATION

The *Employment in 2030* Forecast of Canadian Occupational Growth can be integrated with other sources of labour market information to help inform future projections, data tools, and policy.

This forecast is intended to complement other sources of labour market information, such as the COPS forecast or the Labour Force Survey, to paint a more nuanced and complex picture of future employment. The mixed-method approach of this analysis allows for the inclusion of factors that may be excluded or underestimated in traditional labour indicators and forecasts.

By using various sources to prepare for possible futures, governments, researchers, and program delivery organisations can better equip themselves to identify and overcome potential challenges and take advantage of opportunities.

NEXT STEPS

The Forecast of Canadian and Occupational Growth (FCOG) and analysis in *Ahead by a Decade* presents a national picture of what employment may look like in Canada in 2030. Along with the previous reports and resources released as part of BII+E's *Employment in 2030* project, it outlines the trends, risks, and opportunities for Canada's workers in the next decade. The data used for this analysis also provides more granular snapshots of where those opportunities might lie and, in so doing, offers additional guidance for policymakers, researchers, employers, and educators.

In order to enable further exploration, users can engage with the research through an interactive data visualization. The application allows a high level of interaction, and a closer look at specific regions, identities, and other demographic factors that may be of interest. The datasets and code created in this analysis will also be available for download on the Brookfield Institute GitHub. Researchers can use these resources to continue to study changes in the Canadian labour market and apply this forecast to tackle additional questions.

POSSIBLE EXTENSIONS

There are interesting extensions that would complement the research conducted through the *Employment in 2030* initiative. Policymakers, researchers, and service providers could leverage the project's outputs and forecast in order to:

+ Integrate the forecast into the design of existing or new policies, programs, and tools, such as regional economic development and industrial policies, mid-career retraining programs, and digital tools for helping workers identify job pathways, and use it to drive the development of the partnerships required to help workers and employers navigate the forecasted changes;

+ Examine the identified trends and their potential effects in more detail for specific contexts such as industries, regions, or demographic groups, to design policy and program responses;

+ Apply the *Turn and Face the Strange* trends in the development of future scenarios for use in policy and planning, in order to identify preferred futures and take steps to achieve them;

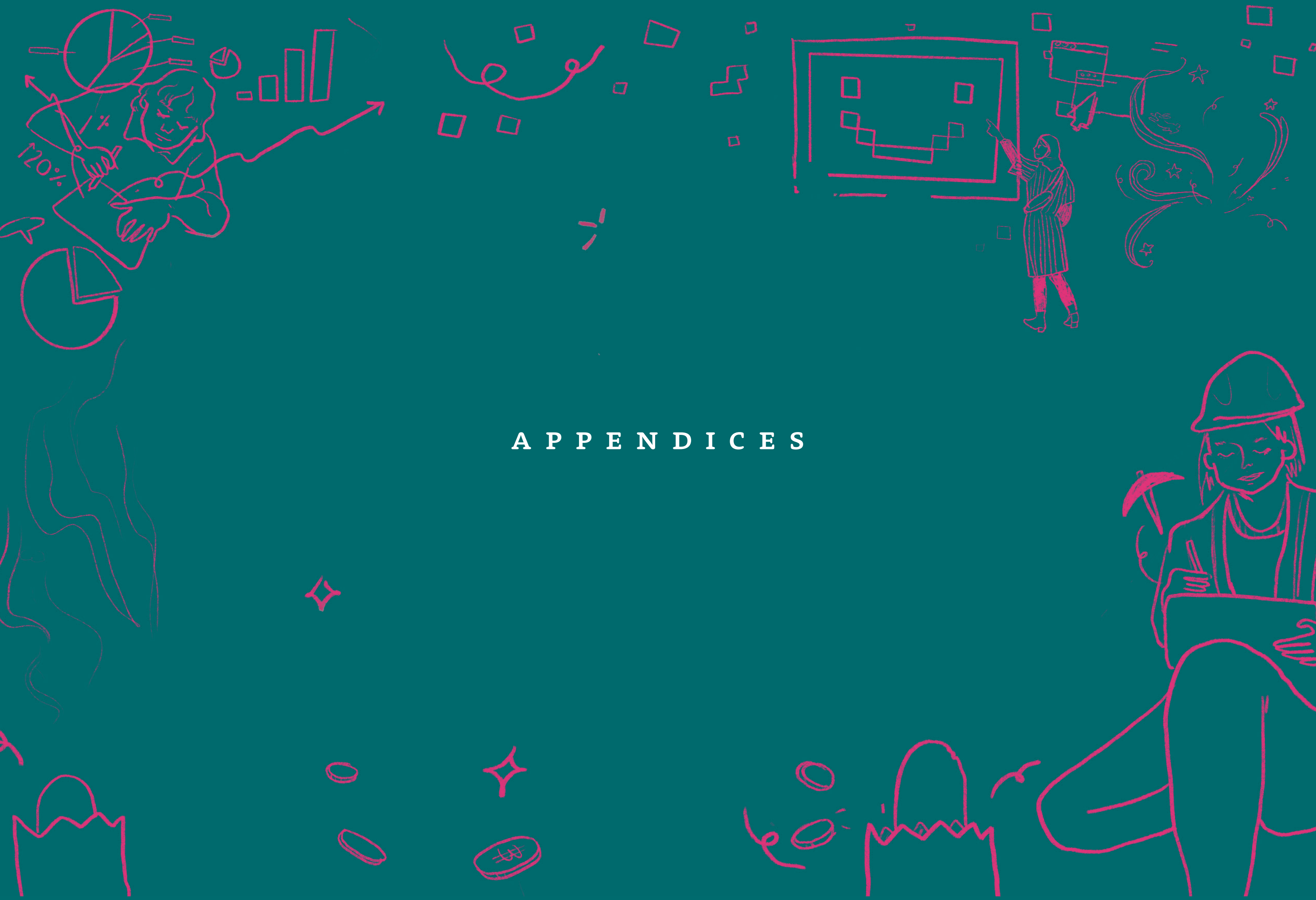
+ Investigate existing or design new curricula to teach the foundational, or other complementary skills and abilities in K-12, post-secondary, or informal education environments, as well as build tools for measuring levels of skill and ability attainment;

+ Delve into more granular and intersecting demographic layers to evaluate the resilience of different groups of workers, for example across rural and urban divides, or for intersectional identities;

+ Recalibrate a future iteration to use the Skills and Competencies Framework recently released by ESDC.[157] The Labour Market Information Council, Statistics Canada and ESDC are considering options for mapping these skills to occupations, and a skills taxonomy that is explicitly mapped to Canadian occupations may provide a picture of future employment that is better balanced to reflect unique features in the national labour market; and

+ Replicate this study in future years, to continue to offer a forecast that complements regular projections such as COPS.

Through the Employment in 2030 initiative, BII+E offers a picture of what the future of Canadian employment could look like. By creating an additional source of labour market information, it aims to inform the design of resilient policies, programs and tools that will position workers and employers to better navigate a labour market that is changing in ways that past experience may not always be able to predict.



APPENDICES

APPENDIX A: DATA AND PREPARATION

O*NET SKILLS, KNOWLEDGE, AND ABILITIES DATA

The O*NET database is a US-based labour market information project, which provides worker and job information for over 900 US occupations. It consists of hundreds of standardized descriptors, which are publicly accessible, and is consistently updated using survey information from a range of workers in each occupation.[158] O*NET scores are often used in skills and labour literature to examine the attributes of workers and jobs in a given occupation.[159] Since the purpose of this study is to create projections and insights driven by worker traits, the O*NET categories considered come from the worker-oriented aspect of the taxonomy. In particular, this study uses O*NET's **abilities, skills, and knowledge** descriptors.

For each feature in these categories, O*NET provides both an importance and a level score. They are both informed by O*NET's surveys and highly correlated.[160] [161] However, similarly to the approach used in Nesta's *The Future of Skills: Employment in 2030*, only importance scores and not level scores are used, given the latter's high rate of recommended suppression.[162] Importance scores range from 1 to 5, as the possible ratings range from *Not Important* (1) to *Extremely Important* (5).[163] However, the level scores pose an additional comparability challenge since the definitions of each score (1-7) vary by feature. As a result, this analysis is driven by the importance of possessing an ability, skill, or knowledge base and uses only the importance scores for each trait.

As described above, a crosswalk developed by BII+E was used to translate these scores to Canadian occupations. The crosswalk and the accompanying methodology are available in Connecting the Dots: Linking Canadian Occupations to Skills Data.[164] However, for many occupations, a 1:1 mapping between Canadian and US occupations is not possible. There are many more US occupations than Canadian ones, and multiple Canadian codes may map to only one O*NET code. For the purpose of the random forest model, these scores were rounded to reduce prediction error.

OCCUPATION SELECTION

Benchmark occupations

Benchmark occupations were those chosen to be discussed by experts in all workshops. They were selected on the basis of providing the widest representation of skill, knowledge, and ability combinations across Canada. Using the skill, knowledge, and ability (SKA) importance scores from O*NET for each occupation, selection occurred in two stages: 1) singular value decomposition (SVD) was used to cut the number of features down from 120 to 21 decorrelated variables, and 2), K-Means clustering was used to divide occupations into 15 clusters in the skills, knowledge, and abilities vector space.

The occupations that were finally selected are those most representative of the space, namely the occupations closest to the centre of those 15 clusters. It is important to note that 15 occupations were excluded from this exercise due to missing attribute values from O*NET, making the set of occupations 485 instead of 500. These vectors are missing because they are new occupations, because they are military occupations, or because they encompass a varied group of occupations not elsewhere classified which makes the identification of important attributes difficult for survey respondents.

Singular value decomposition (SVD) is the generalization of eigen decomposition used for any real or complex matrix. SVD allows an exact representation of any matrix, but also makes it easy to eliminate the less important parts of that representation to produce an approximate representation with any desired number of dimensions. Like eigen decomposition, singular value decomposition produces a matrix of eigenvectors and a set of corresponding eigenvalues. Dimension reduction is then done by ordering the eigenvalues, selecting the top n and then building a matrix out of the corresponding eigenvectors. We selected 21 vectors which together represent 90.73% of the variation in the data.

Given an initial set of k *means* in a vector space, the k-means algorithm uses the following process to generate clusters: 1) to create the initial clusters, every object (in this case an occupation) is associated with the nearest mean; 2) means are then recalculated as the actual centroid of each of those clusters; 3) clusters are then redefined, where each object belongs to the cluster represented by the new mean they are the closest to; and 4) the means are then recalculated and the process begins again. This process iterates the groupings until objects stop changing clusters (and convergence is reached). Using the SciKit Learn methodology, initial *means* are selected using the k-means++ algorithm.[165] Final clusters comprise occupations with similar activities and skill requirements. For example, one cluster includes most managerial codes while another is comprised of occupations in education and social service provision.

Finally, in order to select representative occupations, those closest to the centre of each cluster were identified. In the case of a tie between occupations, those with the highest employment were selected. However, there were also cases where additional criteria were necessary to ensure that high quality responses were gathered from our workshop participants. The next closest occupation was used as the benchmark occupation when:

1. The occupation selected through this process included jobs “not elsewhere classified” (e.g. other professional engineers not elsewhere classified). The lack of specificity in both the occupational description and the associated skill profile would not lead to a useful participant assessment.

2. The historical employment data for the occupation selected through the process was affected by changes in the national classification. If the employment estimates were inflated because of changes in the 2011 NOC structure, the graphs provided to participants may have deterred and misguided participants. We also considered this issue with regional occupations.

Regional occupations

An occupation’s regional importance is determined by aggregating three measures:

1. **Regional employment share:** the percentage of employed workers in the region who are employed in the occupation.

2. **Regional quotient:** Regional employment share of an occupation divided by its national share.

3. **Regional concentration:** The percentage of each occupation’s national employment present in the region.

For each occupation and each metric, the percentile that an occupation falls into is calculated. Those percentile scores are then weighted to create an aggregate score for the occupation. Regional employment share percentile accounted for 50% of the score, regional quotient for 30%, and regional concentration for 20%. A simple average gave a high weight to small regional occupations that actually employed very few people, such as hunter and gatherers with 600 employees. However, it is important to acknowledge regional importance relative to national, which is why 50% of the total measure is still the second and third criteria.

WORKSHOP DETAILS

Before rating, participants were introduced to 31 trends with the potential to impact Canada's labour market in the next 10-15 years. These trends emerged through foresight analysis and are presented in *Turn and Face the Strange*, the first report in the Employment in 2030 series. A foresight game designed specifically for the workshops encouraged participants to think broadly and imaginatively about how a range of different trends might intersect to impact occupation employment and skills demand as well as familiarizing them with occupational definitions, and labour market baseline information. The game materials and description are available in the BII+E blog entry *How to Design a Workshop for the Future of Employment*. [166]

Participants rotated through 20 occupation stations in small groups, where facilitators presented key occupational information. Of these 20 occupations, 15 were the benchmark occupations described above and 5 were regional and specific to the workshop. See Phase 2: Workshops- Workshop inputs for a list of the information provided. Participants then submitted one of the survey cards shown in Figure 1. The card asks them to respond to questions regarding the top trends affecting employment in an occupation and how employment in the occupation would change in absolute and proportional terms by 2030.

Figure 1: **Workshop survey card**

Participant ID: 03 - 01
Occupation: Financial managers

1. **List up to 5 trends that will affect the number of individuals employed in this occupation. Circle the direction of their net effect:**

   ______________ ↑ ↓
   ______________ ↑ ↓
   ______________ ↑ ↓
   ______________ ↑ ↓
   ______________ ↑ ↓

2. **In 2030, there will be more / the same / fewer workers in this occupation.**

3. **In 2030, this occupation's share of total employment in Canada will:**
   - ☐ Increase
   - ☐ Remain constant
   - ☐ Decrease

4. **How comfortable are you with your answer?**
   1 - 2 - 3 - 4 - 5 - 6 - 7 - 8 - 9 - 10 (Most Comfortable)

Additionally, participants were asked to provide a rating of how comfortable they were with their answers given the information they had. The question was designed as a tool to make participants feel more comfortable with uncertainty and ambiguity as a result of workshop design feedback. It is not as a measure of how confident participants were in their prediction, as such a response may be affected by personal factors such as personality, rather than certainty in the labour market. As a result, these scores were not included in the model.

EXPERT SURVEY DATA

Table 1 is a summary of the portion of experts who gave a certain response to a question for an occupation. For example, the occupation with the highest portion of experts projecting growth is chefs. In terms of absolute change, 100% of experts agreed that chefs would grow in terms of employment and 89% agreed there would be growth in terms of employment share.

Historically, using census information for the rated occupations, share and absolute changes move in the same direction. For context, approximately 89% (40 occupations) experienced matching directional changes in absolute and share terms from 2011-2016 as well as from 2006-2011. This is less pronounced but still dominant in the 2001-2006 period, where approximately 70% of the 45 occupations matched. The survey data shows that experts believe these trends may continue.

Table 1: **Summary of responses**

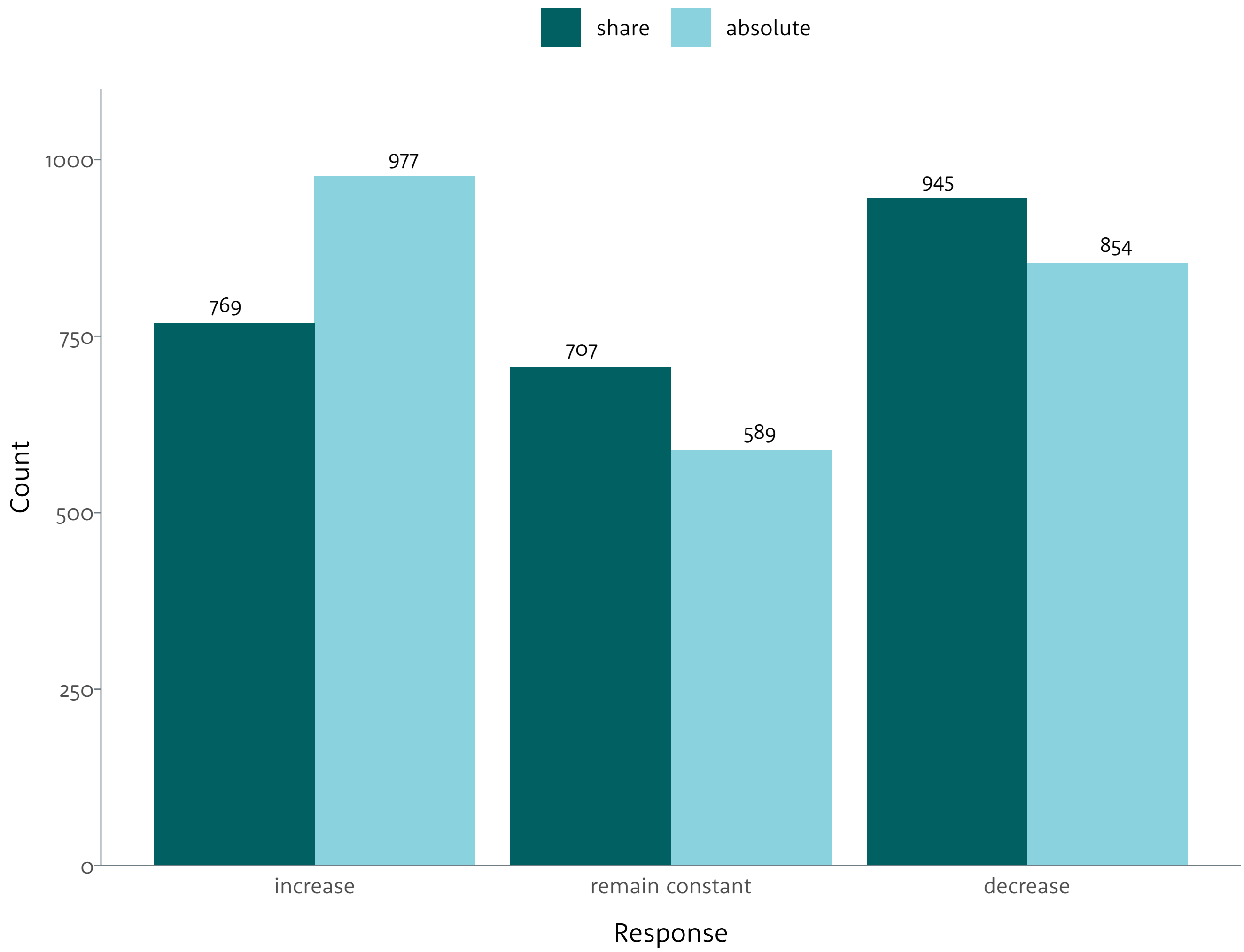
Question:	"Change in Share"			"Absolute Change"		
Answer:	Increase	Constant	Decrease	More	Same	Fewer
Minimum Portion	0%	5%	0%	0%	0%	0%
Mean Portion	34%	31%	35%	44%	24%	32%
Maximum Portion	89%	76%	91%	100%	57%	96%
Standard Deviation	0.26 percentage points	0.16 percentage points	0.27 percentage points	0.28 percentage points	0.13 percentage points	0.26 percentage points

Responses on growth in absolute employment versus share of employment

As mentioned above, participants answered how they thought employment would change in both absolute and proportional terms for each occupation. Responses often indicated a similar direction of change, but diverged in 20.6% of responses. Figure 2 presents a count of answers for both types of questions. The highest number of projections for absolute growth are *increase*, while the highest number for proportional growth is *decrease*. Additionally, there are more answers indicating no change for the proportional growth question than the absolute. If Canadian employment is expected to increase overall, many occupations will grow in absolute terms but fewer in proportional terms. The more interesting and perhaps subtle question is which occupations will grow at a higher rate than total employment. On this question, experts seemed to think a smaller number of occupations would stand out.

Table 2 illustrates each participant's response, including their answer for absolute growth (left) versus their answer for growth in share (top). The significant areas of divergence are participants who think an occupation will grow in absolute terms but not more than other occupations are growing (i.e. the 223 responses indicating both more in absolute terms and *constant* in terms of share). There are also a number of participants who think an occupation will remain constant in absolute terms but be overtaken by the growth of others (i.e. the 133 responses indicating both same in absolute terms and *decrease* in terms of share).

Figure 2: **Count of expert answers, by direction and question**



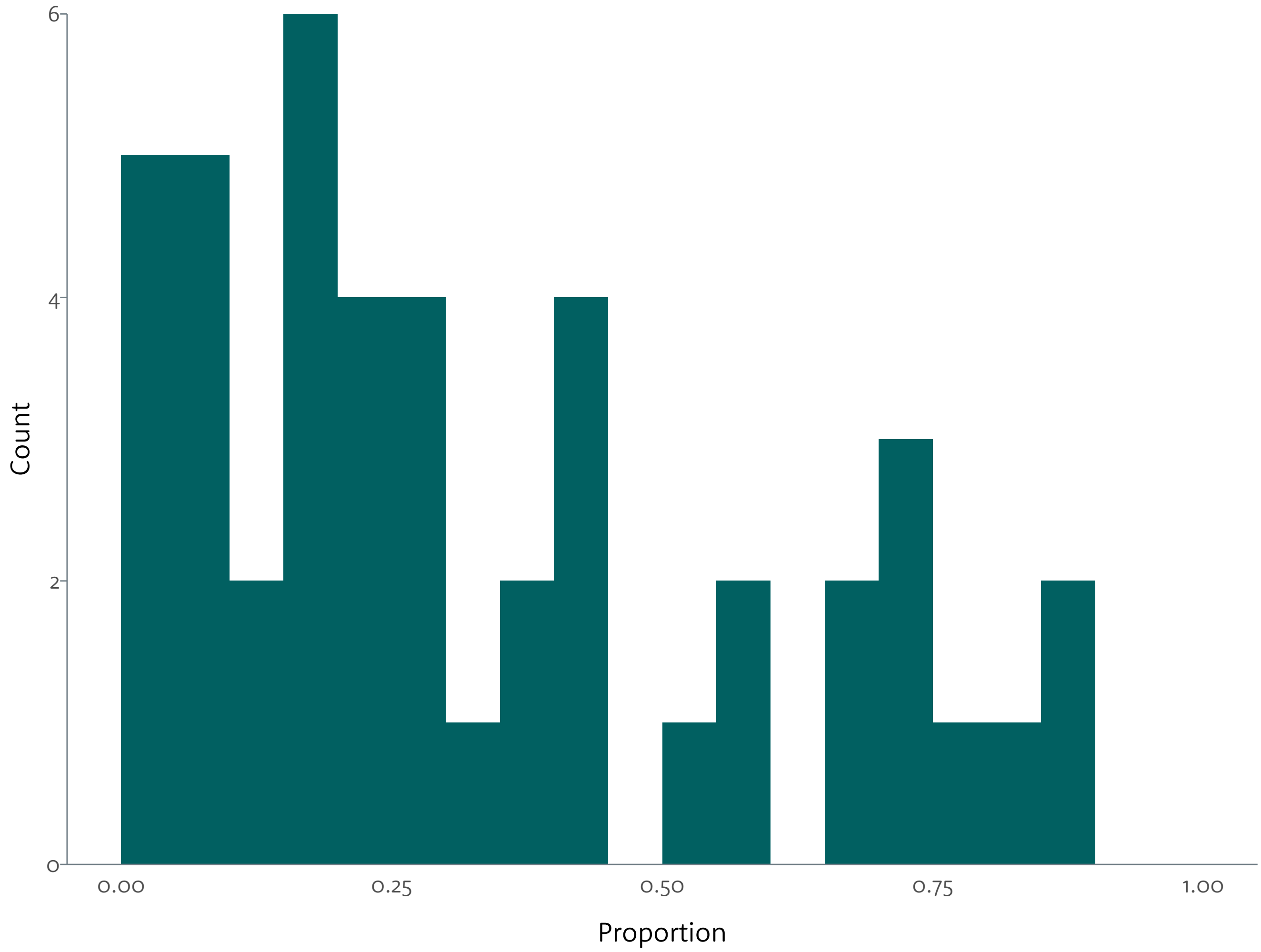
Source: BII+E analysis

Table 2: **Response combinations**

Answer to Share --------------- Answer to Absolute	Increase	Constant	Decrease
More	722	223	32
Same	37	419	133
Fewer	9	65	780

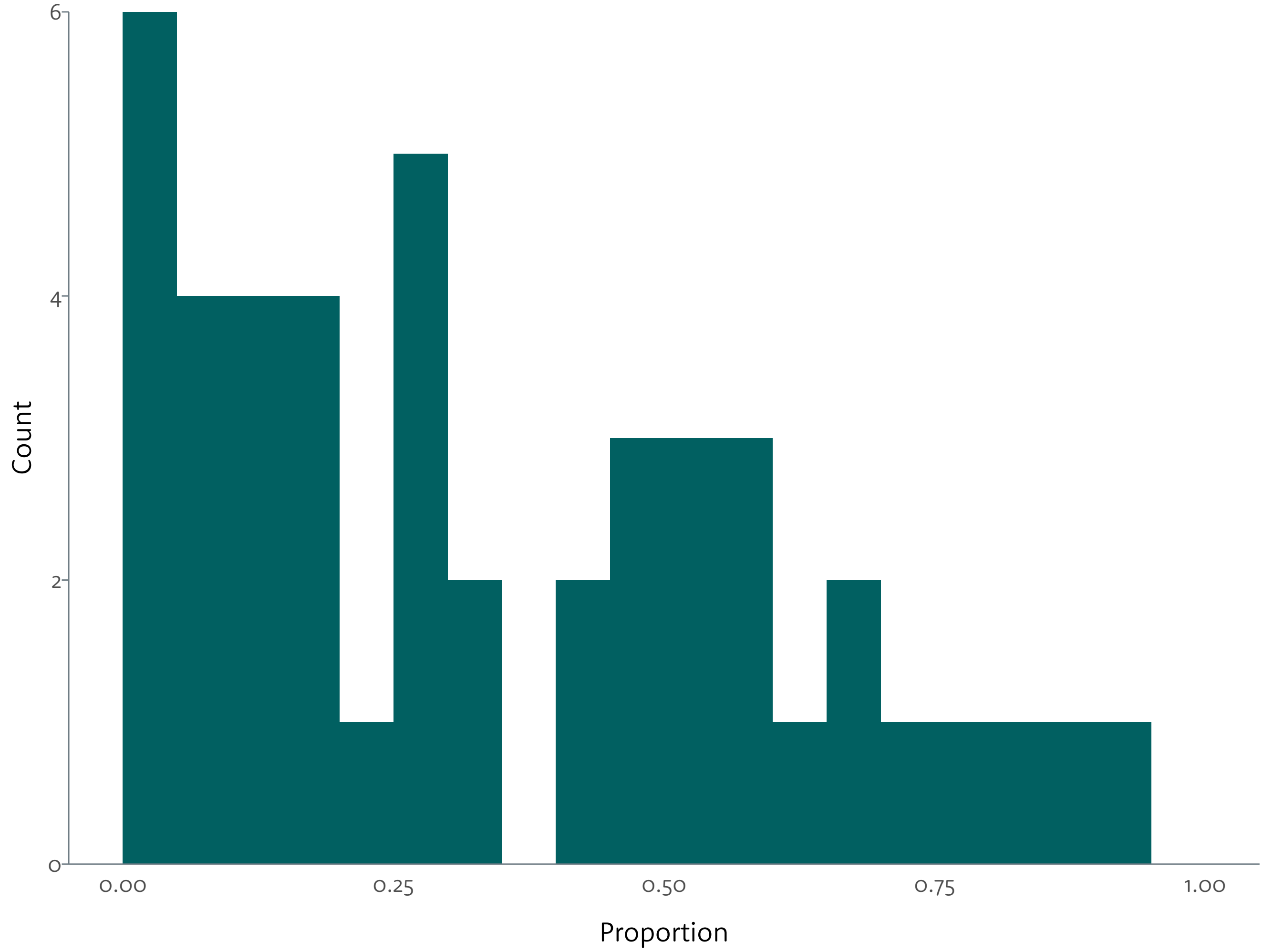
Figure 3 shows the distribution of the proportion of experts who gave an *increase* response to the share question and Figure 4 shows the same for *decrease*. Both are fairly similar, left skewed distributions.

Figure 3: **Distribution of the proportion of experts who projected increase in share for an occupation**



Source: BII+E analysis

Figure 4: **Distribution of the proportion of experts who projected decrease in share for an occupation**



Source: BII+E analysis

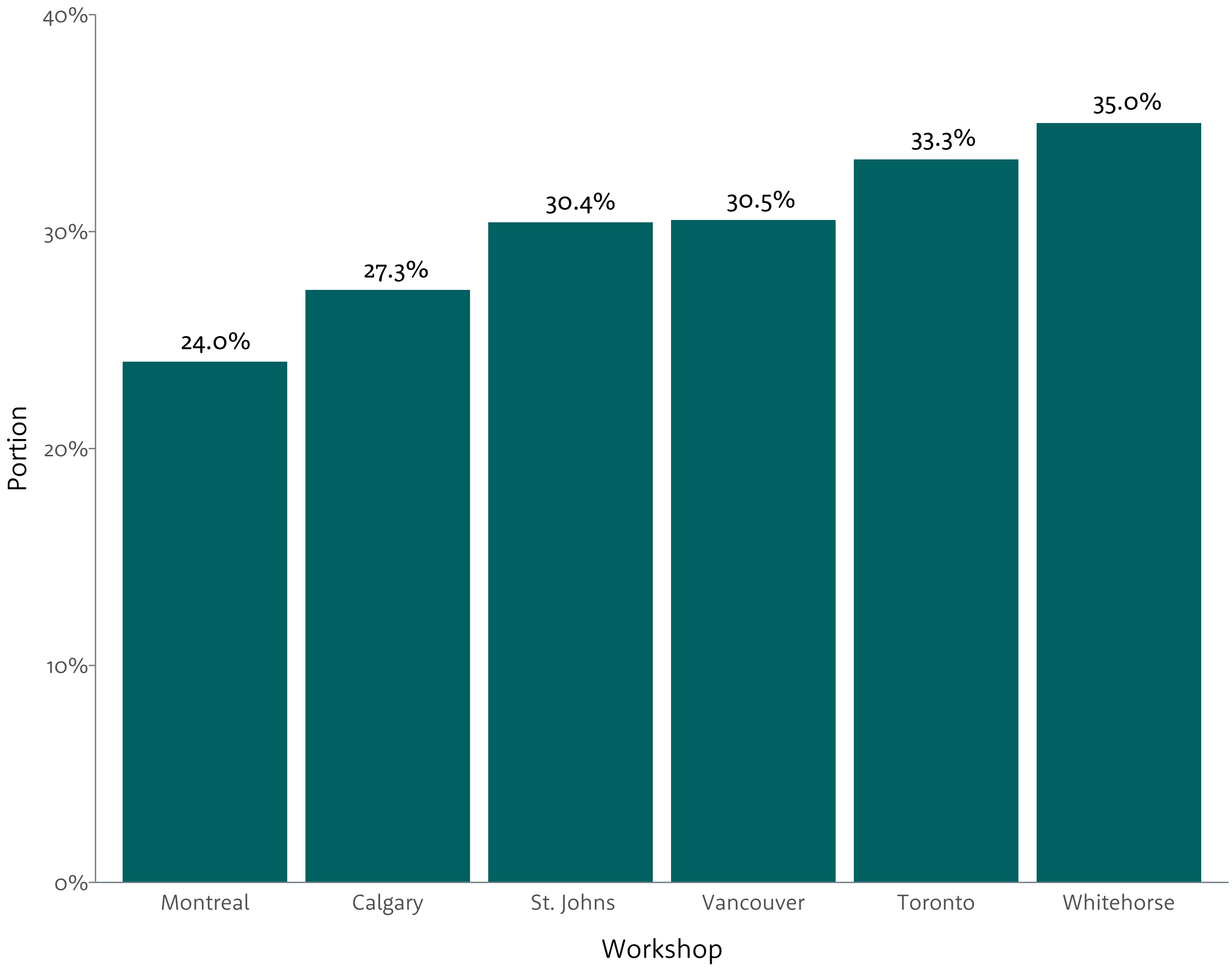
Regional ratings variation

There are expected differences in how experts in different workshops (and thus cities) classified benchmark occupations. As shown in Figure 5, across occupations there is a difference of 10 percentage points in how often participants rated an occupation as growing. Montreal participants gave *increase* responses to the share question 25% of the time whereas Whitehorse participants gave this answer 35% of the time.

Figure 6 shows the largest disagreements are for supervisors in petroleum, gas, and chemical processing and utilities, as well as operators and attendants in amusement, recreation, and sport.

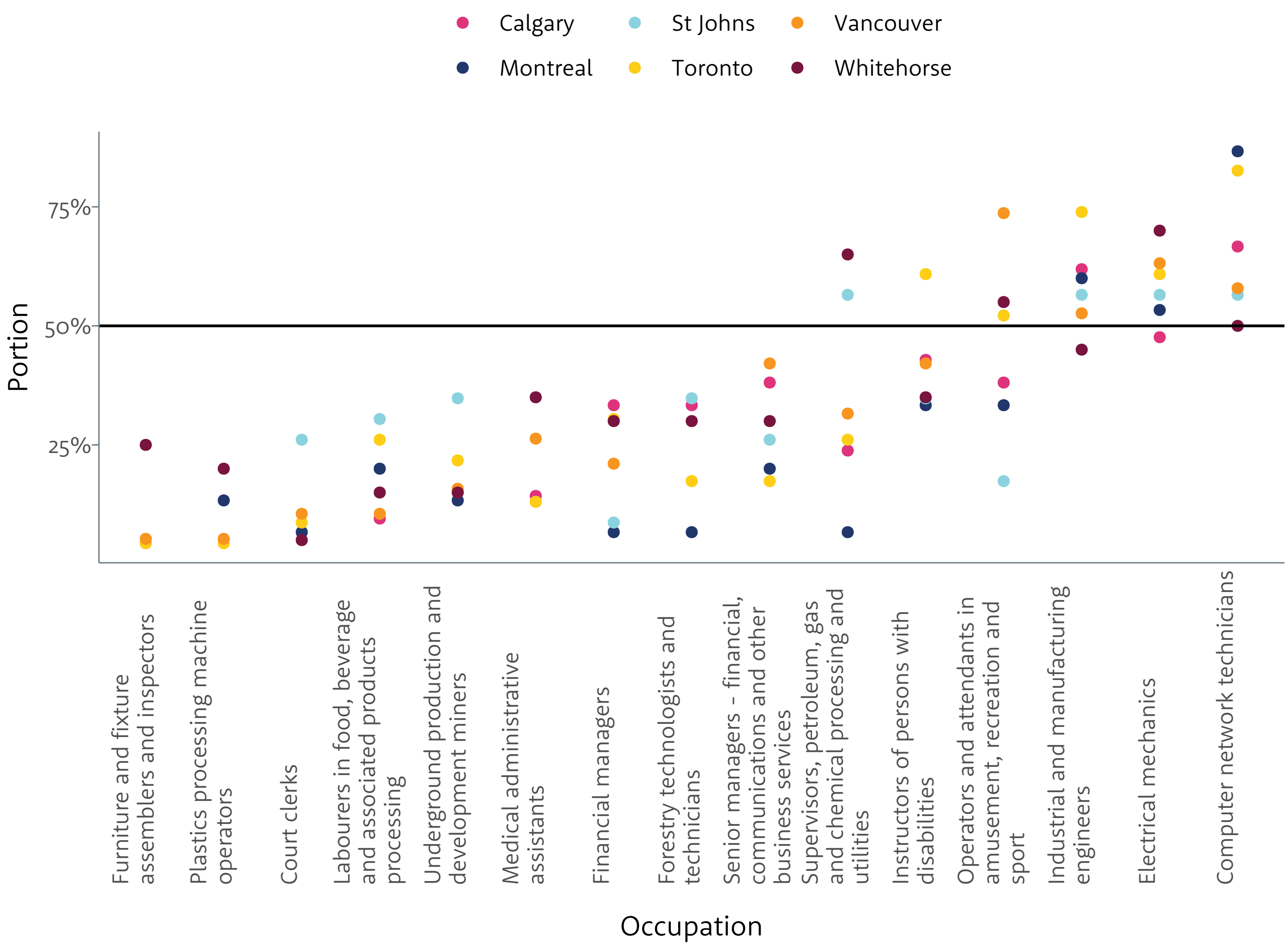
For supervisors in petroleum, gas, and chemical processing and utilities, Vancouver, Calgary, and Toronto are largely in agreement with 25-30% of experts rating the occupation as growing. However, in Whitehorse and St. John's the majority of experts rated the occupation as growing. In Montreal, experts were almost all in agreement that this occupation would not grow. From discussions in the workshops it became evident that some of the uncertainty may be derived from the fact that 14% of workers in this occupation are employed in the mining, gas and oil industries, which has seen shocks in recent years. For operators and attendants in amusement, recreation, and sport, Vancouver's was the only workshop in which a large majority of experts rated the occupation as growing. On the other side of the spectrum, only 19% of participants in St John's rated it as such. These differences may reflect differences in regional employment trends or differences of perspective but for most occupations there was relative agreement.

Figure 5: **Portion of participants who projected increase in share, by workshop**



Source: BII+E analysis

Figure 6: **Portion of participants who projected decrease in share, by workshop**



Source: BII+E analysis

APPENDIX B: MODEL DETAILS

MODEL SELECTION

A range of modelling approaches were considered, including Gaussian processes, other Bayesian approaches, and support vector machines. Random forests, however, had a number of advantages that made them ideal for this problem. They can be used not only for classification but for probability prediction of a category (see next section). Random forests output a robust metric of feature importance and also allow for the detailed examination of feature interactions, something that is not possible in other models. One can also use them for regression (in this case to predict the continuous portion of experts who give a specific answer) however the regression approach was less accurate. Another reason the random forest method was selected is that one of the goals of this study is to identify which skills are the most important for how an expert rates an occupation and this approach makes it easier to extract feature interactions. The decision was ultimately based on model accuracy, with random forests performing significantly better than other models.

Learning problem and setup

Given an occupation represented by a vector of skill, knowledge, and ability (SKA) scores, what is the distribution over answers that experts would have given, based on survey data?

Our model is trained on data where every observation is an expert projection for an occupation. There are 120 unique workshop occupation pairs (See Appendix A) each with (roughly) 20 experts, which amounts to 2,420 observations. The x vector is a list of SKA importance scores for an occupation and y is an expert answer. Note that any observation that is the same occupation has the same x vector. See Testing Method below for details on how this is handled.

RANDOM FOREST

The random forest model was built and implemented using SciKit Learn, a free machine learning library for the Python programming language.[167] Random forests are built by creating a number of decision trees based on subsamples of the data and outputting an aggregation of their predictions. In this case, the decision trees are a series of yes-no questions where each step (or node) is designed to best split the data into two possible categories. For example, for a split based on the importance score of originality, if an observation had a score less than 2.5 (out of 5) it went into one node and if not, the other. Ideally, this split would make it so the majority of the observations were cleanly divided and the observations in one node had the *increase* label, and in the other the *not increase* label.

The metric used for this is gini impurity, and is based on the probability of a sample being labelled incorrectly if it was randomly labelled according the distribution of samples organized into that node. For example, if a node was 80% *increase* then there would be an 80% chance that an observation in that node would be labelled *increase*. The gini impurity of a node is then the probability that a randomly chosen sample in that node would be incorrectly labeled. In this case there is an 80% chance that 20% of the node would be incorrectly labelled, so the gini impurity is 0.16.

Given two classes, *increase* and *not increase*, $P_{increase}$ is the portion of observations in a node that has the true label of *increase*. Gini impurity is then:

$$P_{increase}(1-p_{increase}) + (1-p_{increase})P_{increase} = 2P_{increase}(1-p_{increase}))$$

At every node, the algorithm finds both the feature and threshold on that feature for the greatest reduction in gini impurity. Resulting impurity is an average impurity of the two resulting nodes weighted by the number of samples that are in them.

The probability estimate given by a leaf node (for samples that fall into that leaf node) is the portion of samples that are positive in that leaf. If the tree has no restrictors, like maximum number of levels, or minimum number of data points in a leaf, a tree will grow until every leaf is pure, i.e. the probability in the leaf is one (or the gini impurity is 0). In this case, restrictors were necessary to reduce the risk of overfitting. All model parameters were chosen to optimize performance and, as a result, most leaf nodes are not pure, but rather give a probability prediction. For the whole forest, the predicted probability of an observation is the mean of the probabilities in each leaf where the observation is present.

Trees are built using two types of sampling from the dataset. First, for each tree a random subset of features is used—in this case a number of features equalling the square root of the total number. Second, a random subset of samples is selected *with replacement* to create each tree (bootstrapping).

Parameter selection for the model was done through gridsearch, where each set of parameters was tested using Group K Fold testing (see the Testing method section for more details). The parameters selected can be found in Table 3.

Table 3: **Random forest parameters**

Parameter	Value
Criterion	gini
Number of trees	250
Max features	sqrt(total features)
Minimum samples in a leaf	8
Minimum samples in a split node	10
Max depth	none

TESTING METHOD

Performance in all discussions of the model is calculated using mean absolute error (MAE) and tested using the group k-fold method. MAE is the absolute difference between two continuous variables. In this case, it is the difference between the predicted probability of an expert projecting a certain outcome and the true probability. K-fold is an algorithm often used when there is not enough data to perform a simple split into training and testing sets (neither set has enough population information).

Group k-fold is a variant on this procedure where one defines groups (in this case, occupations that experts are classifying) and ensures that no samples from the same group appear in different folds. This is important because the x vector for each observation is a vector of importance scores representing an occupation. As a result, two observations on the same occupation have the same x vector. For example, if the model was trained on 50% of the observations for chefs and then tested on the remaining 50%, it could just memorize the answer distribution for chefs and then output that distribution, not necessarily learning underlying patterns. This is known as data leakage. The group k-fold algorithm ensures that the model is never trained on observations on which it is then tested.

FEATURE SELECTION

Feature importance

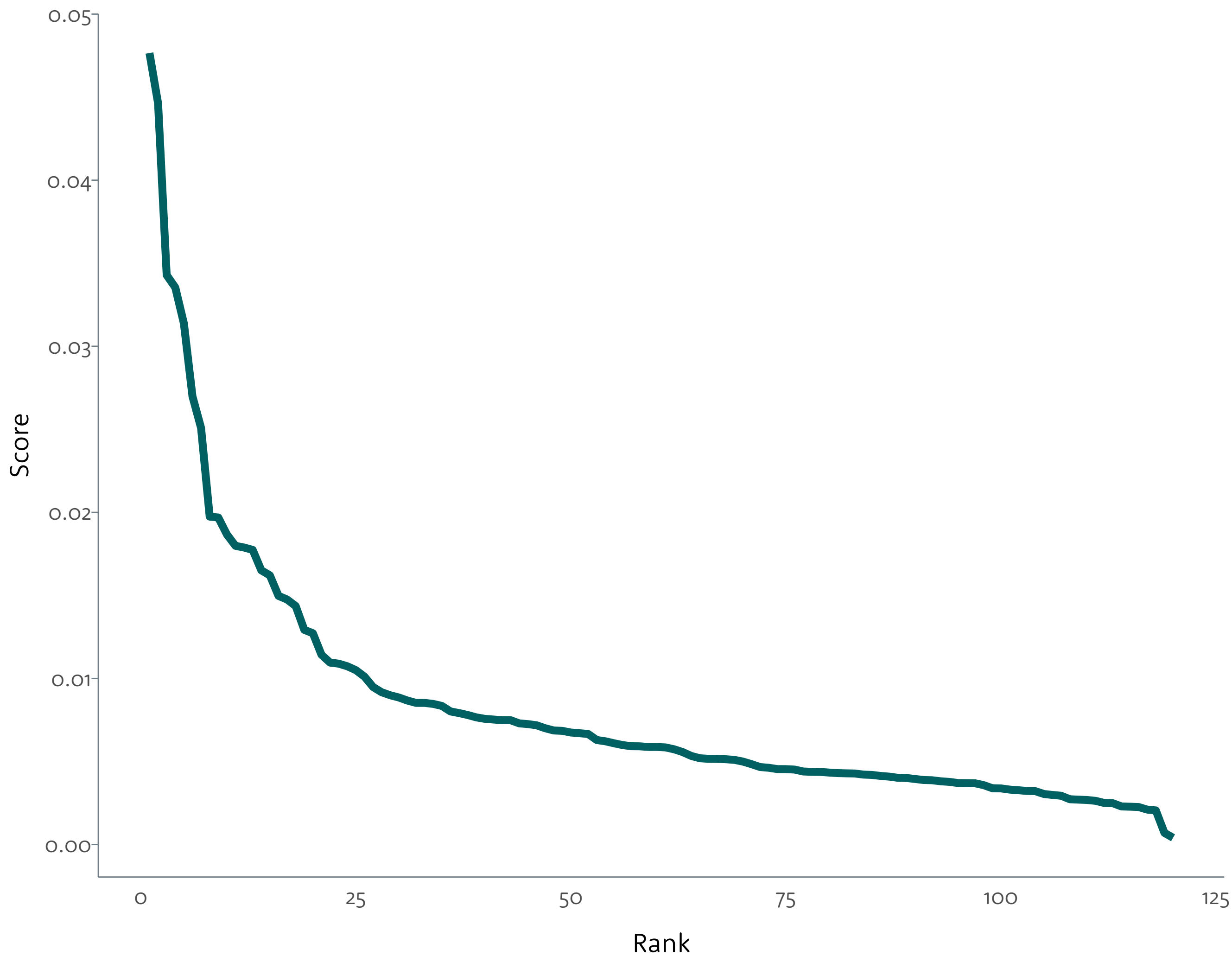
Feature importance is a simple and important output of a random forest that is a useful first place to look for feature selection. As described above, at every node a feature is chosen to maximize the reduction in gini impurity for the next layer. The impurity of the next layer is the average of the impurities of both nodes on that layer weighted by the number of samples in those nodes. The importance of each feature then is defined as the average reduction in impurity caused by that feature, these importance scores are then normalized, adding up to one. Table 4 shows the top 20 features (out of 120) and Figure 7 shows the decline in importance in the ordered scores. As shown, feature importance tapers off first around 10 features and then again around 20.

Table 4: **Feature importances**

Feature	Importance Score
Persuasion	0.05
Fluency of ideas	0.04
Systems evaluation	0.03
Computers and electronics	0.03
Memorization	0.03
Originality	0.03
Service orientation	0.03
Technology design	0.02
Transportation	0.02
Instructing	0.02
Systems analysis	0.02
Customer and personal service	0.02
Design	0.02
Law and government	0.02
Visualization	0.02
Chemistry	0.01

Feature selection was attempted by taking this ordered list of features and adding until performance (as determined by group k-fold MAE) started decreasing. Unfortunately, while this did improve performance, it was not by a significant amount and it was negligible compared to the improvement created by other selection algorithms.

Figure 7: **Ranked feature importance scores**



Source: BII+E analysis

Sequential Forward Floating Selection (SFFS)

The algorithm that was selected is called Sequential Forward Floating Selection (SFFS).[168] It operates as follows: 1) starting with no features, add the feature that improves performance the most; 2) check if dropping any feature currently in the set improves performance; and then 3) repeat. The algorithm was run to check feature counts anywhere between 1-30 features. Given the random element of this model, it was necessary to ensure that the set of skills, knowledge, and abilities the SFFS algorithm selected was stable. In order to test for stability, it was run 20 times, and the best-performing model then generated the predictions presented in this report. Stability was measured through counting how many times the skills in that set were in the other 19 chosen sets. The feature selection process was performed for both the *increase* and *decrease* models independently; Tables 5 and 6 list the features chosen.

Increase model features

Table 5: **Selected features—Increase model**

Feature	# of SFFS Runs Present	Importance Score
Service orientation	20	0.12
Computers and electronics	20	0.15
Chemistry	19	0.09
Information ordering	19	0.04
Monitoring	17	0.04
Time sharing	17	0.06
Management of material resources	13	0.04
Flexibility of closure	13	0.02
Persuasion	8	0.13
Memorization	6	0.11
Finger dexterity	5	0.07
Learning strategies	3	0.04
Far vision	3	0.03
Biology	2	0.06

Decrease model

Table 6: **Selected features—Decrease model**

Feature	# of SFFS Runs Present	Importance Score
Computers and electronics	19	0.14
Category flexibility	17	0.04
Fluency of ideas	12	0.23
Chemistry	10	0.09
Flexibility of closure	9	0.04
Selective attention	9	0
Memorization	7	0.07
Critical thinking	6	0.05
Customer and personal service	4	0.24
Systems evaluation	2	0.1

APPENDIX C: MODEL ANALYSIS

MODEL PERFORMANCE

Table 7: **Model performance**

Measure	Increase	Model
Mean Absolute Error (MAE)	0.126	0.126
Binary prediction accuracy	89%	84%
Quaternary prediction accuracy	67%	64%
ROC AUC	0.90	0.90

Table 7 presents the results of all performance tests described in this section. As described above, the main metric of performance used is Mean Absolute Error (MAE). Both the model predicting the probability that an expert would project growth and the one predicting the probability that an expert would project decline for an occupation had the same MAE of 0.126. This is a fairly low error rate, especially when the primary sorting used in the report is into binary buckets. This is evident in the high accuracy of binary prediction but, as expected, accuracy decreases when trying to classify into four buckets. The ROC AUC (described below) is quite high, with the maximum possible being a score of 1.

Distribution of truth vs prediction for the training set

Though the models output a continuous probability, the predictions are often used to classify an occupation into growing and shrinking labels. To test how well this is done, the true distribution of probabilities is compared to the predicted probability distributions created by both the *increase* and *decrease* models. Tables 8 and 9 are confusion matrices that show how accurately both models place occupations above and below a 0.5 cut-off. As shown, the accuracy of the *increase* model is 89% while the accuracy of the *decrease* model is 84%. Both models overall do quite well but have a high false negative rate. In other words, they classify occupations below 0.5 that should be classified above. The *decrease* model performs somewhat better here at the cost of having some false positives. It is worth noting that many predictions of the *increase* model that should have been over 0.5 were very close to the threshold. An exploration of why certain occupations were misclassified is in the Occupations with the highest error section below.

As one would expect, accuracy decreases if trying to bin into more categories. Tables 10 and 11 are a confusion matrix for categorising occupations into four instead of two bins. For the *increase* model, there are no predictions of over 0.7 for any occupation, although the training set includes seven occupations in this range. The model yields its lowest performance with predictions between 0.3 and 0.5, which have an accuracy of 33% and some of the true values being above 0.7. Accuracy is similar for the decrease model, though it is slightly better. Figure 8 is a histogram showing the true and predicted distribution for the *increase* model. Figure 9 presents this data for the *decrease* model.

Table 8: **Binary increase projection confusion matrix**

	Predicted Increase	Predicted not Increase	Correct portion
Increase	7	5	58%
Not Increase	0	33	100%
	100%	87%	89%

Note: An occupation is projected to grow if the model predicts that at least 50% of experts would classify it as increasing in terms of employment share by 2030.

Table 9: **Binary decrease projection confusion matrix**

	Predicted Decrease	Predicted not Decrease	Correct portion
Decrease	9	5	64%
Not Decrease	2	29	94%
	81%	85%	84%

Note: An occupation is projected to decline if the model predicts that at least 50% of experts would classify it as decreasing in terms of employment share by 2030.

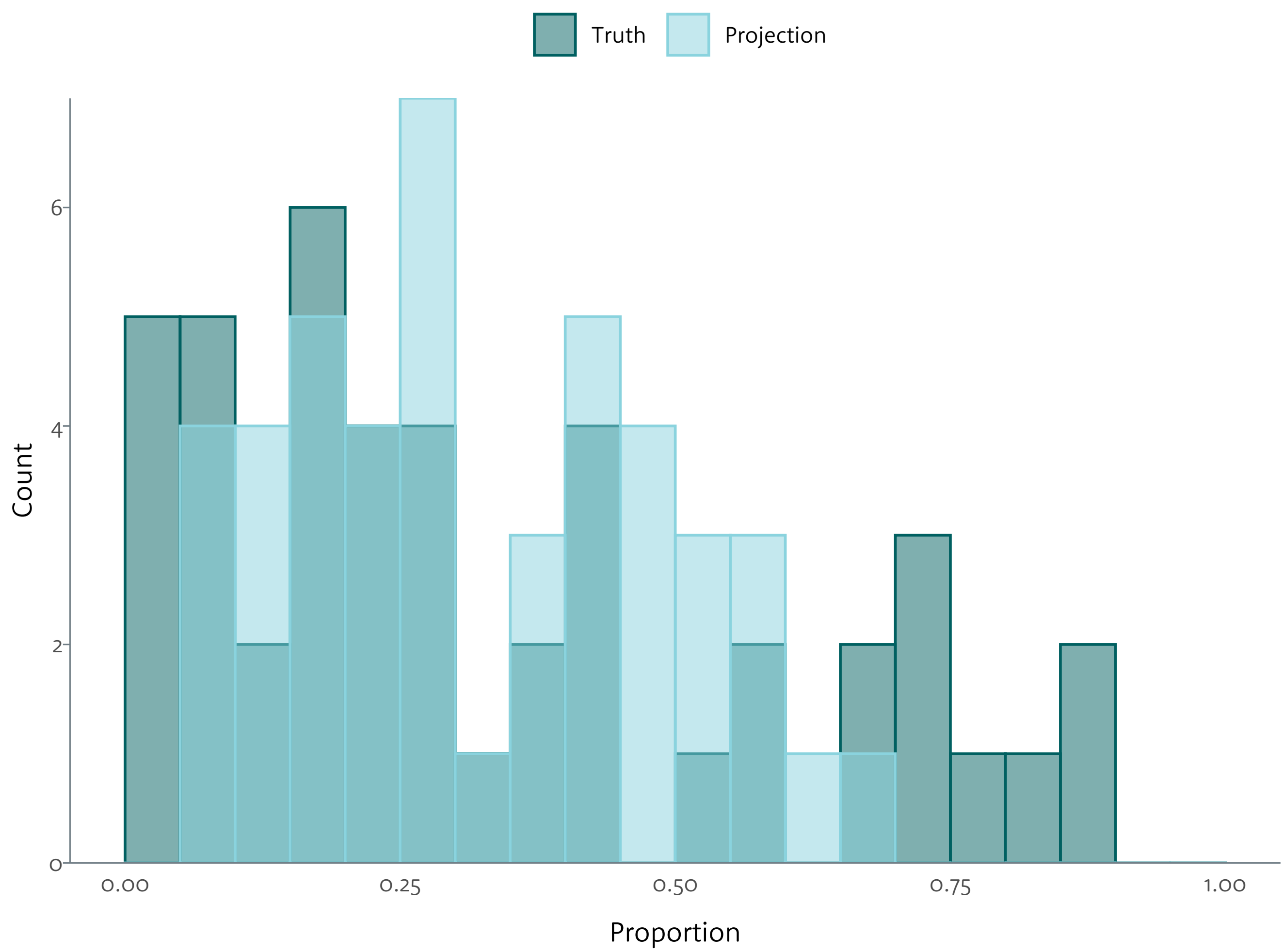
Table 10: **Quaternary increase projection confusion matrix**

Increase Model Prediction -------- True Portion	Greater than 0.7	Between 0.5 and 0.7	Between 0.3 and 0.5	Less than 0.3	Proportion of occupations correctly classified given true range
Greater than 0.7	0	2	4	1	0%
Between 0.5 and 0.7	0	5	0	0	100%
Between 0.3 and 0.5	0	1	5	2	63%
Less than 0.3	0	0	6	19	76%
Proportion of guesses that were correct	NA	63%	33%	86%	67%

Table 11: **Quaternary decrease projection confusion matrix**

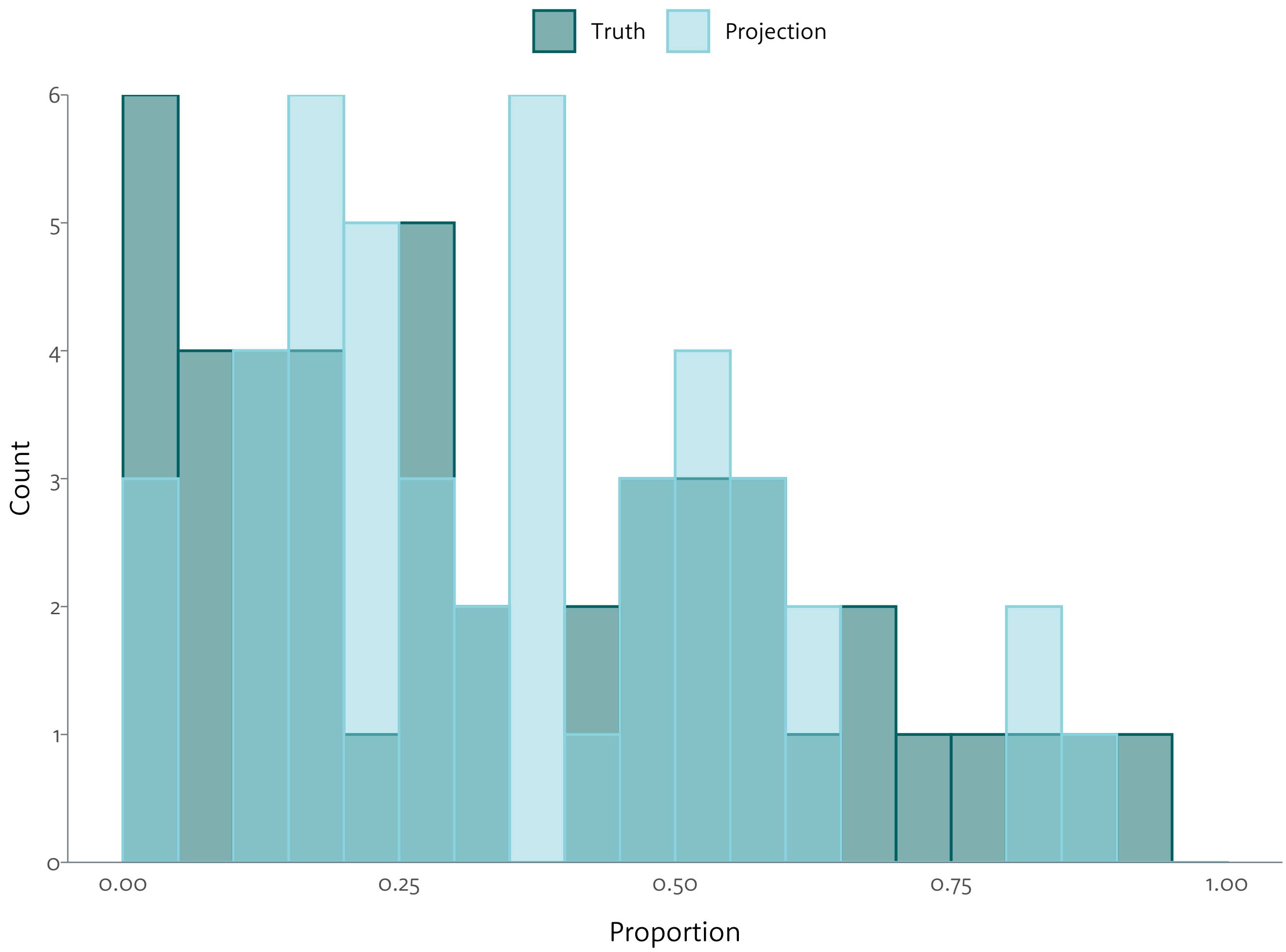
Increase Model Prediction -------- True Portion	Greater than 0.7	Between 0.5 and 0.7	Between 0.3 and 0.5	Less than 0.3	Proportion of occupations correctly classified given true range
Greater than 0.7	3	1	1	1	50%
Between 0.5 and 0.7	0	5	3	1	56%
Between 0.3 and 0.5	0	2	4	1	57%
Less than 0.3	0		5	19	79%
Proportion of guesses that were correct	100%	63%	31%	86%	69%

Figure 8: **True and predicted distribution of the proportion of experts who projected increase in share for an occupation**



Source: BII+E analysis

Figure 9: **True and predicted distribution of the proportion of experts who projected decrease in share for an occupation**



Source: BII+E analysis

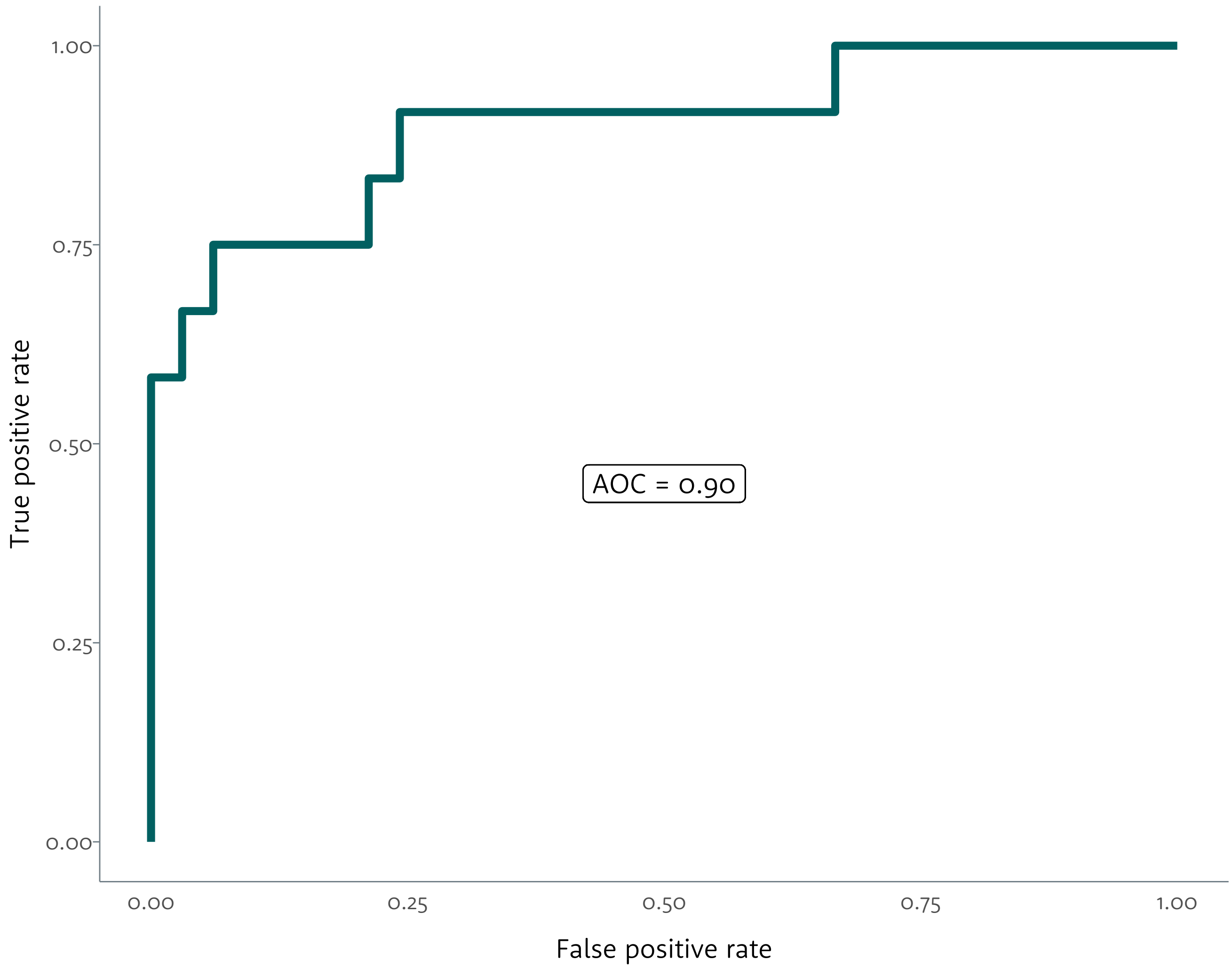
Receiver Operating Characteristic (ROC) curves

Receiver Operating Characteristic curve (ROC) curve is a plot that illustrates the performance of a classifier. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. Using the **Area Under the Curve (AUC)** of an **ROC** curve is a standard performance metric of classifiers and was the main metric employed in Nesta's *Future of Skills: Employment in 2030* to evaluate performance. **ROC AUC** varies from 0.5 to 1, with 0.5 indicating that the model is choosing randomly and 1 indicating perfect prediction. Figures 10 and 11 show the *increase* and *decrease* models both have a score of 0.90.

Occupations with the highest error

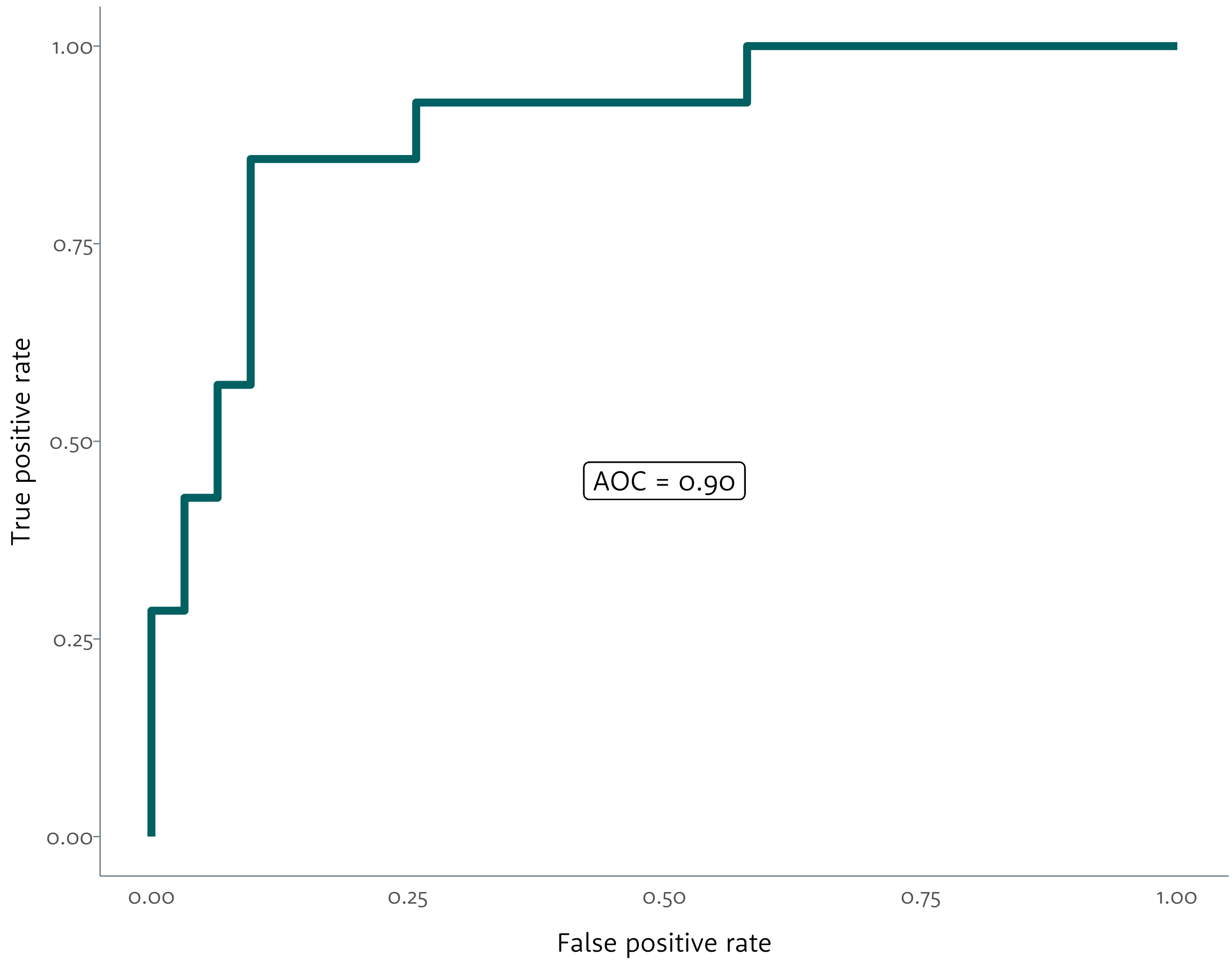
It is difficult to test why the models find some occupations more difficult to predict than others. It may be reasonable to hypothesize that the occupations that are the most difficult to predict are ones where the ratings are less related to the worker attributes of an occupation as determined by O*NET. Experts could expect some occupations to undergo a structural transformation in the next decade, making the SKA traits identified by the taxonomy less relevant.

Figure 10: **Receiver operating characteristic curve for the increase model**



Source: BII+E analysis

Figure 11: **Receiver operating characteristic curve for the decrease model**



Source: BII+E analysis

Increase model

The occupations in table 12 are those with the highest mean absolute error. They are regional occupations, which were only rated in one of the six workshops. As a result, some of the discrepancies seen below may be due to a lower number of observations.

Decrease model

As in the case of the *increase* model, most occupations in Table 13 are regional occupations, and some of the discrepancies seen below may be due to a lower number of observations.

Table 12: **Occupations by Mean Absolute Error (MAE) of projection—Increase model**

NOC	Mean Absolute Error [0-1]	True Probability	Predicted Probability
Light duty cleaners	0.55	0.73	0.19
Airline ticket and service agents	0.43	0.05	0.48
Graphic designers and illustrators	0.42	0.89	0.47
Chefs	0.41	0.89	0.48
Technical sales specialists—wholesale trade	0.34	0.74	0.4
Cooks	0.31	0.73	0.42
Carpenters	0.29	0.45	0.16
Oil and gas well drillers, servicers, testers, and related workers	0.25	0.05	0.3
Health policy researchers, consultants, and program officers	0.25	0.78	0.54
Store shelf stockers, clerks, and order fillers	0.21	0.07	0.27

Table 13: **Occupations by Mean Absolute Error (MAE) of projection—Decrease model**

NOC	Mean Absolute Error	True Probability	Predicted Probability
Airline ticket and service agents	0.48	0.7	0.22
Oil and gas well drillers, servicers, testers, and related workers	0.41	0.76	0.35
Cooks	0.29	0	0.29
Delivery and courier service drivers	0.23	0.27	0.5
Graphic designers and illustrators	0.23	0	0.23
Financial managers	0.22	0.48	0.26
Heavy-duty equipment mechanics	0.2	0	0.2
Carpenters	0.17	0.2	0.37
Painters and decorators (except interior decorators)	0.17	0.11	0.27
Shippers and receivers	0.15	0.73	0.58

GAUSSIAN PROCESS COMPARISON

The Gaussian model built and used for comparison in this report differs from Nesta's in important ways. Notably, this study did not collect confidence scores, so the additional modelling done around those is not present. The Kernel used for the Gaussian process (GP) was a combination of both Matern52 and a linear kernel. The linear kernel is added to counteract the tendency of the Matern52 to move towards 0 when seeing data outside of the area covered by the training set. Additionally, and unlike the random forest, SKA importance scores were left continuous and then scaled and normalized. Finally, feature selection was not used for this model as it worsened performance.

The Gaussian process was tested using the same group k-fold method described above and the same performance metrics were calculated. The MAE for the GP is 17.8 percentage points, which is worse than the random forest model by 5.2 points. Similarly, the **ROC AUC** is 0.64, worse than the random forest model by 0.26 points. On average, the absolute difference between occupation projections is 18.8 percentage points. This is substantial, but is in line with the model's overall MAE. Note that a model predicting probability of decrease was not run for the GP model, so these results are only for probability of growth projections.

Table 14 shows the mean absolute difference between projections generated by the GP and random forest models, by broad occupational category. The highest disagreement is for natural and applied sciences and related occupations, as well as health occupations. This is interesting given that these are the groups with the highest portion of growing occupations. The lowest disagreement is for management occupations, as well as occupations in manufacturing and utilities.

Table 14: **Mean absolute difference between random forest and Gaussian process projections by broad occupational category**

Category	Mean Absolute Difference
Management occupations	0.14
Business, finance, and administration occupations	0.19
Natural and applied sciences and related occupations	0.25
Health occupations	0.25
Occupations in education, law and social, community, and government services	0.18
Occupations in art, culture, recreation, and sport	0.17
Sales and service occupations	0.21
Trades, transport and equipment operators, and related occupations	0.17
Natural resources, agriculture and related production occupations	0.18
Occupations in manufacturing and utilities	0.14

CANADIAN OCCUPATIONAL PROJECTION SYSTEM (COPS) COMPARISON

Tables 15 and 16 are confusion matrices showing the extent to which this approach agrees with COPS forecasting. The majority of the misalignment comes from COPS predicting growth much more often. The model in this analysis predicts growth only 26% of the time that COPS does. As stated in *One Step Ahead*, this disagreement comes from the experts and not a distortion created by the model. This is evident due to the fact that the agreement rate for participant answers among those who were shown COPS projections in the workshop had almost exactly the same disagreement rate as the model (56% agreement vs 53%).

VARIABILITY OF NOC PROBABILITY PREDICTIONS

To ensure that the results are stable given the random elements of the model, the random forest was run 10 times and results were compared. Specifically, the absolute difference between all run pairs was calculated, then the mean of those differences, and finally the mean and standard deviation across occupations. The resulting mean difference was 0.013 and the deviation of differences was 0.006. The maximum difference in any NOC prediction was only 0.028. Overall, these results suggest that the score an occupation receives is quite stable.

Table 15: **Model—COPS confusion matrix**

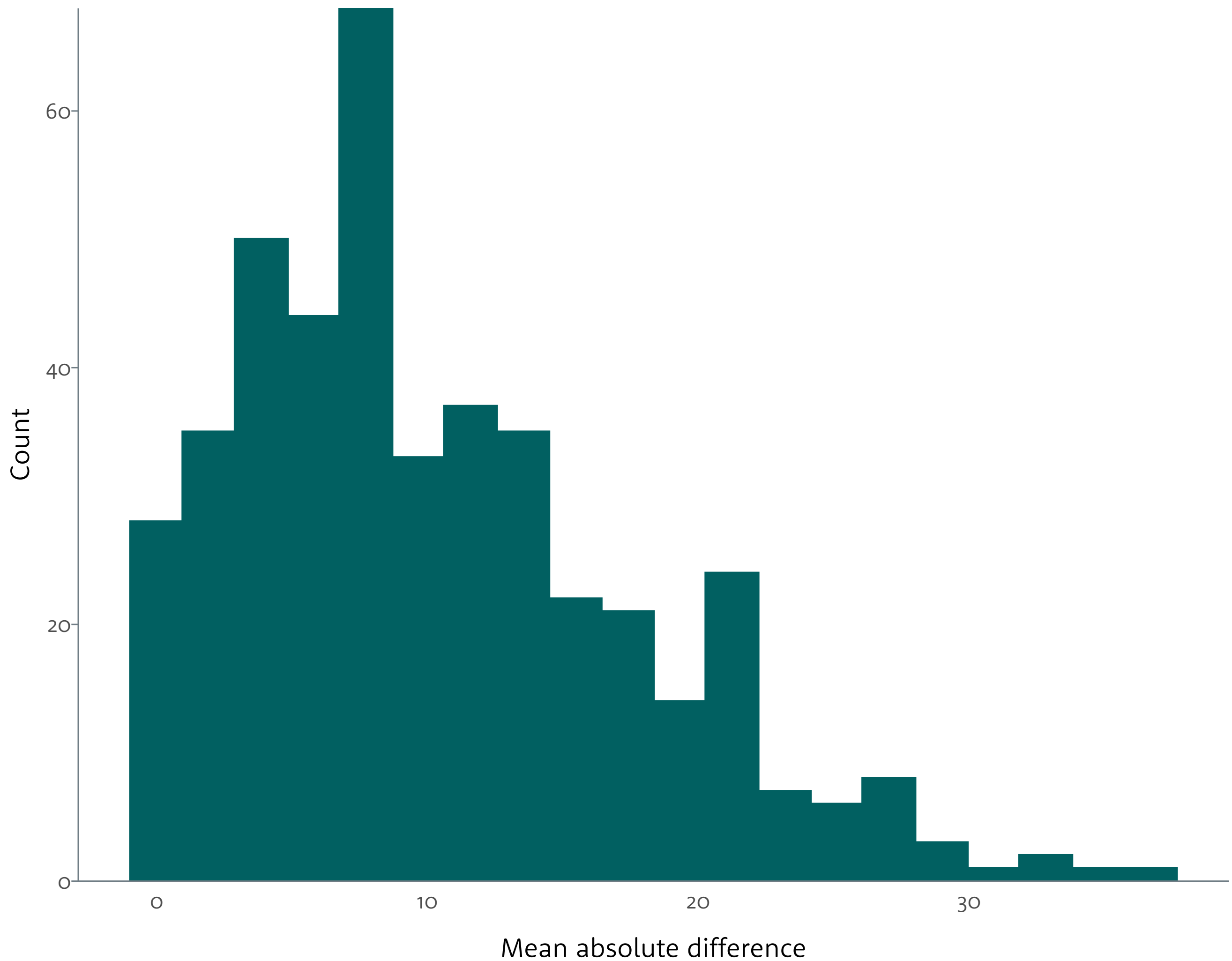
All occupations	COPS—increase	COPS—not increase	COPs agreement
Model—increase	39	22	64%
Model—not increase	107	123	53%
Model agreement	26%	84%	56%

Table 16: **Training occupations—COPS confusion matrix**

Training occupations	COPS increase	COPS not increase	COPS agreement
Model—increase	5	6	45%
Model—not increase	15	19	56%
Model agreement	25%	76%	53%

However, while the change in predicted probability is minimal, it can have larger impacts on an occupation's rank. Using the same procedure as before, it is found that the average difference between the rank of an occupation in different runs is 10.3 (out of 500 NOCs). As a result, rank should be used with caution. Figure 12 is a histogram of those differences.

Figure 12: **Rank variation between model runs for occupations**

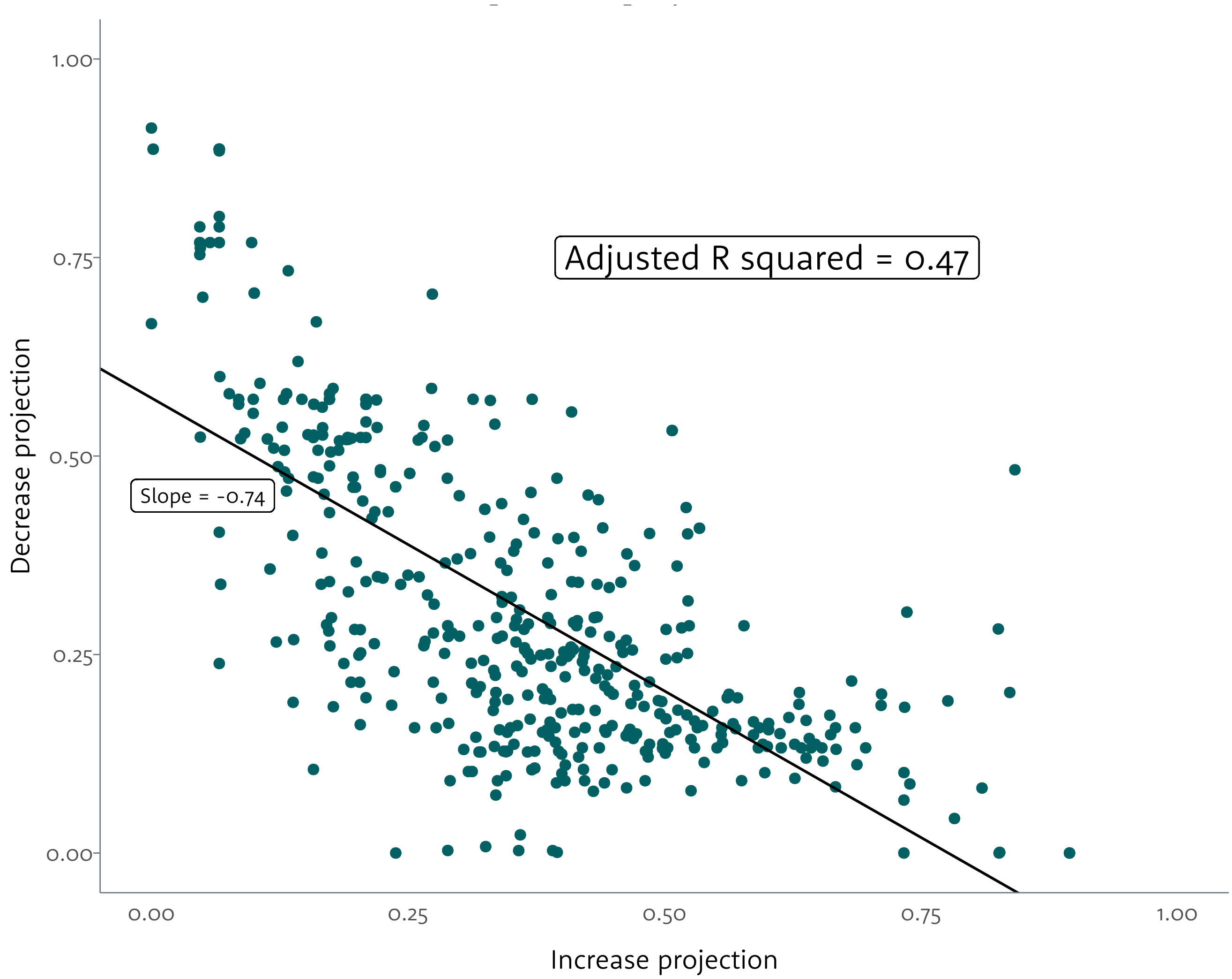


Source: BII+E analysis

COMPARISON OF INCREASE AND DECREASE MODEL PREDICTIONS

The *Employment in 2030* forecast relies on two models: one to predict the probability of an expert classifying an occupation as growing and one to predict the probability of an expert classifying an occupation as shrinking. When exploring how these two predictions compare for each occupation, it is clear that the two inversely follow each other, which is what we would expect. Figure 13 shows the output of the *decrease* model plotted against the output of the *increase* model, with an associated regression. While the relationship is strong, it is comforting that they are not inverses of each other, leaving room for occupations that will neither increase nor decrease.

Figure 13: **Increase vs decrease occupational projections**



Source: BII+E analysis

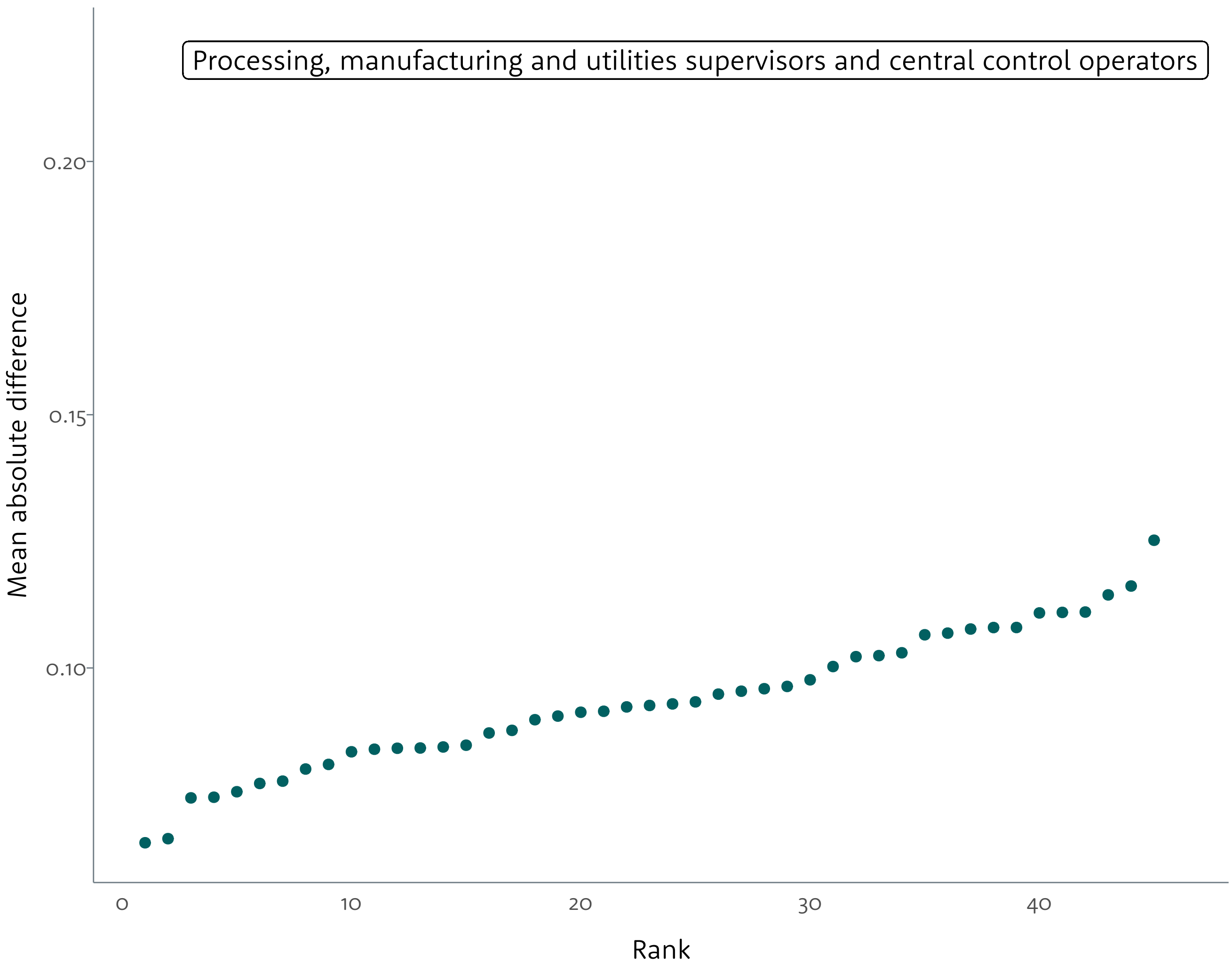
REGIONAL MODELS

Canada's geographical diversity is evident in employment trends and the relative importance of different industries. It is this diversity that motivated the approach of holding regional workshops throughout the country. It also prompted the selection of benchmark occupations that would establish a comparison point between workshops that was consistent between workshops. Some of this variation is explored in the previous *Employment in 2030* report, Signs of the Times, and some of it is inspected here using the benchmark occupations and the random forest model to identify potential differences.

The benchmark occupations of each workshop became the training data for their respective regional models. For example, the Quebec model was only informed by the benchmark occupation ratings gathered from Quebec participants. With six sets of probability estimates, it then became possible to explore potential differences in regional projections. Some differences were already evident in the survey data gathered, which created some expected disparities when expanding predictions to other occupations.[169]

In particular, the models informed by workshops held in Calgary and Montreal tended to predict a higher probability of increase than both the aggregate predictive model and the regional model average. At the same time, those trained on the data from Whitehorse and St. John's tended to generate lower probabilities. Despite these tendencies, the estimates created by the regional models were comparable for all except one major occupation, as Figure 14 shows. The regional estimates generated for processing, manufacturing and utilities supervisors, and central control operators had an extraordinarily high level of disagreement across regional models. The reason for this differential is unclear. It may be due to a regional difference in the level of impact certain trends may have in different regions, such as the differing adoption of automation or alternative energy sources.

Figure 14: **Disagreement between workshops for major occupational groups**



Source: BII+E analysis

STRUCTURAL SKILL INFLUENCE ANALYSIS

This section provides a more detailed description of the structural skills analysis. For each tree in the forest, every path is gathered and placed on a list. Every path is an ordered list of nodes where every node has a feature, a threshold, a direction (either left or right to the next node), and the prediction the model would have given if it had stopped there. This prediction is calculated the same way it is calculated in leaf nodes (See Appendix B: Random forests) and is the number of positive samples over total samples that fall in that node. This list of paths is used to complete the following structural analysis

As described in the main body of the report, this approach aims to find features that **frequently** and **consistently** increased the model's prediction. Another way to think about the model's prediction is that it is a measure of how confident a body of experts would have been about an occupation growing. Therefore, these features are those that consistently increase that confidence. Influence is defined as the percent change in the model's prediction from one node to the next.

When considering interactions between SKAs, feature combinations have a primary feature, a conditional feature, and a conditional direction. The influence of the primary feature is recorded if the path already considered a given conditional feature and went in the specified conditional direction. For example, if one were interested in the influence of persuasion (primary feature), given that instructing (conditional feature) has a high importance (conditional direction), this method would do the following: in the list of all paths, find every instance of persuasion where the path has already gone right on instruction and record the influences on growth projections. This exercise can also be thought of as looking at the influence of a feature in a subspace of the whole feature vector space.

Using the influences for each feature and ordered conditional pairing, the following information is recorded:

1. **Portion of positive influence:** What portion of the influences were positive

2. **Mean positive influence:** For only the positive influences, what was the average percent change

3. **Occurrence count:** The number of occurrences for the feature or pair

As mentioned in the main sections of the report, the criteria for being a foundational trait is stringent. A feature must have exhibited a positive influence portion of over 95% in 10 separate runs. However, other traits are also worth mentioning and their impact is fairly interesting. Table 17 shows all traits that were positive 90% or more in all 10 runs. All of the traits listed have to do with creative and abstract thinking or social skills.

One important aspect of the paths used in the analysis are the thresholds an occupation must have to go right at a split for a particular feature. This can be considered as a metric of a SKA being of sufficient importance to an occupation. Table 17 additionally shows the mean threshold for each consistently important SKA. The most common threshold is 2.5, representing 50% of all thresholds. As the range of scores is 1-5, this is somewhat below average. Particularly, most of the foundational SKAs have typical thresholds at 2.5, the only notable exception being service orientation with an average threshold of 2.9. Of the other notable SKAs, there are some that are particularly high (e.g. active listening), and those that are particularly low (e.g. philosophy and theology). A low typical threshold implies that the standards the model sets for how important a SKA should be for an occupation is lower. For example, for the model to raise an occupation's projection due to customer and personal service, on average that occupation would have to have an importance score above 3.16. For philosophy and theology, on the other hand, an occupation only needs 1.9 on average.

Table 17: **Traits with high portion of positive influence**

	Mean Positive Influence	Mean Portion of positive influence	Mean occurrence count	Mean Threshold	Number of Runs where portion positive influence > 0.95	Number of Runs where portion positive influence > 0.90
Fluency of ideas	0.39	0.96	1618.9	2.54	10	10
Persuasion	0.37	0.97	1687.4	2.56	10	10
Instructing	0.32	0.97	1093.3	2.62	10	10
Memorization	0.31	0.99	1614.9	2.50	10	10
Service orientation	0.3	0.97	1562.6	2.90	10	10
Originality	0.34	0.94	1043.2	2.54	7	10
Systems evaluation	0.34	0.96	1098.3	2.54	6	10
Technology design	0.18	0.96	1311.1	2.11	6	10
Installation	0.15	0.88	356.8	2.10	3	8
Systems analysis	0.34	0.93	874.1	2.59	1	9
Visualization	0.22	0.93	907.1	2.77	1	9
Active listening	0.25	0.87	311.5	3.60	1	8
Number facility	0.32	0.92	692.6	2.52	1	7
Philosophy and theology	0.19	0.88	476.5	1.90	1	7
Fine arts	0.15	0.93	416.1	2.14	1	6
Customer and personal service	0.26	0.9	1179.5	3.16	0	8

Complementary attributes

There are 28,800 possible conditional pairs for which the metrics described above were also calculated. This report focuses on two types of pairings. For both methods, the process was run 20 times and a significance rating was assigned based on how many runs showed the pairing as meeting the criteria. Pairs were sorted first by significance rating and then by average magnitude of positive influence, and the top 3 were selected.

Occupation-specific

For each broad occupational category, SKAs that are important to all occupations within that group were identified. This was done by considering only SKAs where every occupation in the group has an importance score greater than 2.5 and then taking the three with the highest average score. Conditional pairs were then selected so that, given a high score in one of those 3 SKAs, the portion of positive influence for the primary SKA is over 95%.

Knowledge-specific

The second type of pairing was designed to answer a question that focuses on the knowledge traits of the O*NET taxonomy. That is: for which SKAs does having a high score make a certain knowledge have a consistent positive influence? In other words, under what circumstances is a knowledge area useful? For each area of knowledge, conditional SKAs are selected such that the knowledge has a positive impact 95% of the time, given that the occupation has already been determined to have a high score in that skill. The main body described two of these and Table 19 has a more complete list.

Table 19: **Traits that augment knowledge traits**

Augmenting attributes	Knowledge area	Augmenting attributes	Knowledge area	Augmenting attributes	Knowledge area
Computers & electronics***		Number facility**		Psychology**	
Flexibility of closure**	Administration & management	Complex problem solving*	Engineering & technology	Social perceptiveness**	Personnel & human resources
Complex problem solving**		Flexibility of closure*		Originality*	
Auditory attention***		Sales & marketing*		Communications & media***	
Psychology**	Biology	Reaction time*	English language	Mathematics knowledge**	Philosophy & theology
Speech recognition**		Law & government*		Chemistry**	
Rate control**		Depth perception***		Finger dexterity*	
Control precision**	Building & construction	Monitoring***	Fine arts	Mathematics skill*	Physics
Static strength**		Administration & management***		Written expression*	
Social perceptiveness***		Mathematical reasoning**		Education & training**	
Speech clarity***	Chemistry	Speech clarity**	Food production	Speaking**	Production & processing
Therapy & counseling**		Perceptual speed**		Speech clarity**	
Computers & electronics**		Production & processing**		Public safety & security***	
Judgment & decision making**	Clerical	Equipment selection**	Foreign language	Administration & management***	Psychology
Time management*		Problem sensitivity**		Monitoring***	

Augmenting attributes	Knowledge area	Augmenting attributes	Knowledge area	Augmenting attributes	Knowledge area
Near vision**		Judgment & decision making*		Time management**	
Equipment selection**	Communi-cations & media	Economics & accounting*	Geography	Spatial orientation*	Public safety & security
Foreign language*		Time management*		Stamina*	
Problem sensitivity***		Design**		Category flexibility**	
Critical thinking***	Computers & electronics	Reaction time*	History & archeology	Written comprehension*	Sales & marketing
Systems evaluation***		Foreign language*		Active listening*	
Time management**		Static strength**		Speech clarity**	
Personnel & human resources**	Customer & personal service	Category flexibility**	Law & government	Monitoring**	Sociology & anthropology
Deductive reasoning**		Written expression**		Negotiation**	
Speech recognition***		Judgment & decision making**		Mathematical reasoning**	
Speed of closure***	Design	Rate control**	Mathematics knowledge	Visualization*	Telecom-munications
Customer & personal service**		Speech clarity**		Learning strategies*	
Computers & electronics*		Social perceptiveness**		Auditory attention**	
Speech clarity*	Economics & accounting	Active listening**	Mechanical	Systems evaluation **	Therapy & counseling
Law & government*		Psychology**		Problem sensitivity **	
Active listening***		Category flexibility***		Operations analysis**	
Monitoring**	Education & training	Hearing sensitivity**	Medicine & dentistry	Category flexibility **	Transportation
Rate control**		Communications & media**		Night vision*	

Note 1: Foundational skills & abilities are not included in this analysis since they always contribute to an occupation's projection of growth, regardless of its other attribute scores. Note 2: The number of asterisks denote the consistency of the attributes over several runs of the models. Attributes with three stars arise as complementary 15 out of 20 times or more, those with two stars at least 10 times, & those with one are less frequent & may occur as seldom as five times.

APPENDIX D:
NOC PREDICTIONS

The table on the following pages presents the projections generated through this forecast for each of 485 Canadian occupational unit groups. For each occupation the table contains: its National Occupational Classification (NOC) code and title, the predicted portion of experts who project growth or decline, as well as the implied portion of experts who would project no change. Each occupation is shaded to reflect its classification under this forecast. Occupations shaded in green are projected to grow in employment share, those without shading have no projected change, while those shaded red are projected to decline. Occupations shaded in gray have an undetermined projection. In addition, this section provides basic employment information at the national level from the 2016 Census.

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
0012	Senior government managers and officials	0.29	0.28	0.43	18,315	0.10%	$114,932.20
0013	Senior managers–financial, communications and other business services	0.29	0.27	0.44	58,320	0.31%	$215,990.70
0014	Senior managers–health, education, social and community services and membership organizations	0.29	0.28	0.43	26,595	0.14%	$104,171.30
0015	Senior managers–trade, broadcasting and other services, n.e.c.	0.41	0.29	0.30	48,210	0.26%	$159,398.30
0016	Senior managers–construction, transportation, production and utilities	0.29	0.28	0.43	56,825	0.31%	$190,443.60
0111	Financial managers	0.22	0.48	0.30	75,835	0.41%	$105,082.70
0112	Human resources managers	0.23	0.19	0.58	50,825	0.27%	$92,330.30
0113	Purchasing managers	0.42	0.29	0.29	22,080	0.12%	$97,705.40
0114	Other administrative services managers	0.47	0.26	0.28	32,780	0.18%	$90,152.10
0121	Insurance, real estate and financial brokerage managers	0.31	0.24	0.45	29,800	0.16%	$134,031.30
0122	Banking, credit and other investment managers	0.22	0.48	0.29	63,030	0.34%	$101,951.50
0124	Advertising, marketing and public relations managers	0.41	0.26	0.33	68,500	0.37%	$82,786.00
0125	Other business services managers	0.52	0.25	0.23	21,410	0.11%	$73,232.20
0131	Telecommunication carriers managers	0.50	0.19	0.31	14,315	0.08%	$99,343.90
0132	Postal and courier services managers	0.53	0.14	0.33	3,590	0.02%	$65,678.80
0211	Engineering managers	0.71	0.20	0.09	19,785	0.11%	$132,182.60
0212	Architecture and science managers	0.36	0.31	0.33	9,005	0.05%	$108,156.50
0213	Computer and information systems managers	0.57	0.20	0.23	63,715	0.34%	$109,505.90
0311	Managers in health care	0.56	0.20	0.24	32,790	0.18%	$86,934.40
0414	Other managers in public administration	0.27	0.32	0.41	8,820	0.05%	$90,465.90
0421	Administrators–post-secondary education and vocational training	0.39	0.25	0.36	17,705	0.10%	$82,294.10
0422	School principals and administrators of elementary and secondary education	0.44	0.22	0.33	32,280	0.17%	$97,025.50
0423	Managers in social, community and correctional services	0.45	0.23	0.31	30,355	0.16%	$62,575.80
0431	Commissioned police officers	0.49	0.19	0.31	2,065	0.01%	$119,203.00
0432	Fire chiefs and senior firefighting officers	0.63	0.20	0.17	2,500	0.01%	$104,334.00
0512	Managers–publishing, motion pictures, broadcasting and performing arts	0.48	0.18	0.34	7,665	0.04%	$69,800.20
0513	Recreation, sports and fitness program and service directors	0.27	0.54	0.20	12,575	0.07%	$52,573.30
0601	Corporate sales managers	0.40	0.25	0.34	69,575	0.37%	$104,587.10
0621	Retail and wholesale trade managers	0.29	0.00	0.71	391,685	2.10%	$58,311.60
0631	Restaurant and food service managers	0.52	0.17	0.30	128,250	0.69%	$37,596.30
0632	Accommodation service managers	0.42	0.11	0.47	25,835	0.14%	$45,138.30
0651	Managers in customer and personal services, n.e.c.	0.33	0.19	0.47	27,050	0.15%	$37,505.60
0711	Construction managers	0.29	0.29	0.42	83,000	0.45%	$83,417.70

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
0712	Home building and renovation managers	0.29	0.29	0.42	46,485	0.25%	$38,428.70
0714	Facility operation and maintenance managers	0.53	0.41	0.06	58,140	0.31%	$72,931.60
0731	Managers in transportation	0.32	0.29	0.40	34,990	0.19%	$84,972.30
0821	Managers in agriculture	0.14	0.62	0.24	147,370	0.79%	$28,004.30
0822	Managers in horticulture	0.41	0.18	0.41	5,010	0.03%	$36,562.20
0823	Managers in aquaculture	0.35	0.29	0.36	1,250	0.01%	$48,342.30
0911	Manufacturing managers	0.40	0.18	0.42	70,225	0.38%	$96,051.50
0912	Utilities managers	0.58	0.29	0.14	10,355	0.06%	$134,384.30
1111	Financial auditors and accountants	0.51	0.36	0.13	202,195	1.09%	$76,156.30
1112	Financial and investment analysts	0.40	0.24	0.36	53,870	0.29%	$128,368.90
1113	Securities agents, investment dealers and brokers	0.70	0.13	0.17	14,590	0.08%	$131,632.60
1114	Other financial officers	0.63	0.13	0.23	115,730	0.62%	$88,572.80
1121	Human resources professionals	0.39	0.24	0.38	77,525	0.42%	$71,014.20
1122	Professional occupations in business management consulting	0.36	0.42	0.22	79,155	0.43%	$79,942.50
1123	Professional occupations in advertising, marketing and public relations	0.44	0.21	0.35	96,460	0.52%	$54,629.40
1211	Supervisors, general office and administrative support workers	0.34	0.20	0.46	13,555	0.07%	$62,331.10
1212	Supervisors, finance and insurance office workers	0.34	0.20	0.46	19,775	0.11%	$65,687.60
1213	Supervisors, library, correspondence and related information workers	0.56	0.14	0.30	4,460	0.02%	$29,697.10
1214	Supervisors, mail and message distribution occupations	0.53	0.14	0.33	8,640	0.05%	$52,123.20
1215	Supervisors, supply chain, tracking and scheduling co-ordination occupations	0.52	0.29	0.19	48,270	0.26%	$55,992.60
1221	Administrative officers	0.25	0.48	0.27	280,105	1.50%	$49,092.40
1222	Executive assistants	0.48	0.12	0.40	47,055	0.25%	$60,894.50
1223	Human resources and recruitment officers	0.35	0.19	0.46	33,000	0.18%	$54,770.70
1224	Property administrators	0.53	0.41	0.06	44,690	0.24%	$49,029.90
1225	Purchasing agents and officers	0.33	0.54	0.13	47,455	0.25%	$66,888.10
1226	Conference and event planners	0.33	0.23	0.44	25,595	0.14%	$37,300.70
1227	Court officers and justices of the peace	0.27	0.22	0.51	4,835	0.03%	$58,999.80
1228	Employment insurance, immigration, border services and revenue officers	0.41	0.25	0.35	33,135	0.18%	$59,074.80
1241	Administrative assistants	0.25	0.48	0.27	264,970	1.42%	$36,339.60
1242	Legal administrative assistants	0.46	0.38	0.16	40,945	0.22%	$44,020.70
1243	Medical administrative assistants	0.17	0.49	0.34	57,020	0.31%	$34,876.80
1251	Court reporters, medical transcriptionists and related occupations	0.22	0.57	0.21	10,960	0.06%	$31,732.00
1252	Health information management occupations	0.16	0.67	0.17	5,470	0.03%	$55,274.20
1253	Records management technicians	0.35	0.14	0.51	7,655	0.04%	$46,985.20

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
1254	Statistical officers and related research support occupations	0.55	0.13	0.32	4,880	0.03%	$52,458.10
1311	Accounting technicians and bookkeepers	0.16	0.47	0.37	139,960	0.75%	$38,177.40
1312	Insurance adjusters and claims examiners	0.32	0.20	0.48	29,130	0.16%	$60,687.70
1313	Insurance underwriters	0.37	0.10	0.52	15,350	0.08%	$63,979.70
1314	Assessors, valuators and appraisers	0.63	0.19	0.18	11,675	0.06%	$60,430.00
1315	Customs, ship and other brokers	0.36	0.16	0.48	4,195	0.02%	$52,408.70
1411	General office support workers	0.34	0.32	0.34	258,455	1.39%	$33,972.90
1414	Receptionists	0.27	0.28	0.45	167,230	0.90%	$25,009.60
1415	Personnel clerks	0.34	0.27	0.38	12,795	0.07%	$46,820.70
1416	Court clerks	0.10	0.55	0.35	3,050	0.02%	$43,777.80
1422	Data entry clerks	0.29	0.47	0.24	40,345	0.22%	$31,217.90
1423	Desktop publishing operators and related occupations	0.65	0.12	0.23	1,740	0.01%	$49,586.30
1431	Accounting and related clerks	0.16	0.47	0.37	154,205	0.83%	$41,168.30
1432	Payroll administrators	0.11	0.59	0.30	36,075	0.19%	$49,602.40
1434	Banking, insurance and other financial clerks	0.13	0.47	0.39	25,565	0.14%	$47,972.40
1435	Collectors	0.41	0.25	0.35	14,840	0.08%	$39,276.50
1451	Library assistants and clerks	0.18	0.59	0.24	18,500	0.10%	$24,834.90
1452	Correspondence, publication and regulatory clerks	0.30	0.37	0.33	25,640	0.14%	$44,772.90
1454	Survey interviewers and statistical clerks	0.40	0.09	0.51	28,505	0.15%	$15,362.80
1511	Mail, postal and related workers	0.16	0.53	0.32	31,785	0.17%	$36,809.00
1512	Letter carriers	0.23	0.43	0.34	30,470	0.16%	$46,924.30
1513	Couriers, messengers and door-to-door distributors	0.40	0.40	0.21	24,750	0.13%	$26,385.50
1521	Shippers and receivers	0.13	0.73	0.13	115,930	0.62%	$35,053.20
1523	Production logistics co-ordinators	0.32	0.15	0.54	26,890	0.14%	$58,565.00
1524	Purchasing and inventory control workers	0.36	0.39	0.26	31,700	0.17%	$38,563.20
1525	Dispatchers	0.39	0.29	0.32	39,625	0.21%	$49,275.40
1526	Transportation route and crew schedulers	0.39	0.19	0.42	6,590	0.04%	$52,739.20
2111	Physicists and astronomers	0.58	0.09	0.33	2,995	0.02%	$88,162.30
2112	Chemists	0.64	0.12	0.24	13,710	0.07%	$70,447.70
2113	Geoscientists and oceanographers	0.39	0.16	0.45	12,105	0.07%	$130,025.70
2114	Meteorologists and climatologists	0.60	0.16	0.24	1,160	0.01%	$79,652.00
2121	Biologists and related scientists	0.67	0.16	0.18	22,135	0.12%	$66,943.60
2122	Forestry professionals	0.46	0.15	0.39	4,740	0.03%	$72,115.40
2123	Agricultural representatives, consultants and specialists	0.38	0.21	0.41	7,115	0.04%	$56,391.70
2131	Civil engineers	0.50	0.24	0.25	58,500	0.31%	$91,926.90
2132	Mechanical engineers	0.63	0.09	0.28	55,090	0.30%	$91,551.60

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
2133	Electrical and electronics engineers	0.50	0.17	0.33	46,890	0.25%	$96,880.40
2134	Chemical engineers	0.67	0.13	0.20	12,515	0.07%	$117,531.40
2141	Industrial and manufacturing engineers	0.59	0.17	0.25	16,820	0.09%	$86,097.70
2142	Metallurgical and materials engineers	0.47	0.14	0.39	2,860	0.02%	$98,894.20
2143	Mining engineers	0.74	0.30	0.00	3,680	0.02%	$126,162.80
2144	Geological engineers	0.74	0.30	0.00	3,015	0.02%	$108,925.50
2145	Petroleum engineers	0.73	0.18	0.08	8,705	0.05%	$174,527.90
2146	Aerospace engineers	0.47	0.15	0.38	6,355	0.03%	$87,909.30
2147	Computer engineers (except software engineers and designers)	0.69	0.11	0.20	23,625	0.13%	$92,020.30
2148	Other professional engineers, n.e.c.	0.60	0.16	0.24	5,030	0.03%	$74,644.70
2151	Architects	0.52	0.40	0.08	16,455	0.09%	$72,885.40
2152	Landscape architects	0.51	0.15	0.34	2,055	0.01%	$60,982.90
2153	Urban and land use planners	0.43	0.28	0.29	12,770	0.07%	$73,935.10
2154	Land surveyors	0.53	0.08	0.40	8,055	0.04%	$79,207.50
2161	Mathematicians, statisticians and actuaries	0.64	0.14	0.21	12,915	0.07%	$93,945.70
2171	Information systems analysts and consultants	0.61	0.13	0.25	161,275	0.87%	$75,749.30
2172	Database analysts and data administrators	0.57	0.16	0.27	21,855	0.12%	$74,397.20
2173	Software engineers and designers	0.50	0.14	0.36	47,970	0.26%	$88,528.50
2174	Computer programmers and interactive media developers	0.36	0.26	0.38	105,280	0.57%	$68,814.60
2175	Web designers and developers	0.65	0.13	0.21	26,295	0.14%	$41,773.40
2211	Chemical technologists and technicians	0.47	0.19	0.34	25,030	0.13%	$54,087.60
2212	Geological and mineral technologists and technicians	0.32	0.24	0.43	9,290	0.05%	$77,390.40
2221	Biological technologists and technicians	0.20	0.25	0.55	10,785	0.06%	$41,588.00
2222	Agricultural and fish products inspectors	0.20	0.22	0.58	4,685	0.03%	$59,948.70
2223	Forestry technologists and technicians	0.21	0.42	0.36	7,590	0.04%	$48,795.10
2224	Conservation and fishery officers	0.38	0.15	0.47	5,370	0.03%	$53,716.20
2225	Landscape and horticulture technicians and specialists	0.12	0.36	0.53	19,795	0.11%	$32,205.70
2231	Civil engineering technologists and technicians	0.28	0.19	0.52	24,780	0.13%	$58,125.40
2232	Mechanical engineering technologists and technicians	0.42	0.16	0.42	22,085	0.12%	$65,679.60
2233	Industrial engineering and manufacturing technologists and technicians	0.64	0.17	0.19	18,070	0.10%	$59,056.90
2234	Construction estimators	0.41	0.29	0.30	22,210	0.12%	$72,374.10
2241	Electrical and electronics engineering technologists and technicians	0.59	0.13	0.28	44,995	0.24%	$64,198.00
2242	Electronic service technicians (household and business equipment)	0.65	0.14	0.22	51,480	0.28%	$45,514.90
2243	Industrial instrument technicians and mechanics	0.20	0.28	0.52	9,875	0.05%	$93,867.40

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
2244	Aircraft instrument, electrical and avionics mechanics, technicians and inspectors	0.50	0.13	0.36	6,395	0.03%	$69,880.60
2251	Architectural technologists and technicians	0.39	0.00	0.61	10,665	0.06%	$50,500.80
2252	Industrial designers	0.34	0.22	0.44	8,930	0.05%	$54,275.50
2253	Drafting technologists and technicians	0.46	0.25	0.29	28,585	0.15%	$51,858.00
2254	Land survey technologists and technicians	0.56	0.15	0.30	5,155	0.03%	$45,990.30
2255	Technical occupations in geomatics and meteorology	0.64	0.13	0.22	8,980	0.05%	$60,661.50
2261	Non-destructive testers and inspection technicians	0.14	0.40	0.46	7,285	0.04%	$81,484.20
2262	Engineering inspectors and regulatory officers	0.07	0.89	0.05	5,810	0.03%	$78,191.30
2263	Inspectors in public and environmental health and occupational health and safety	0.68	0.22	0.10	34,895	0.19%	$71,533.10
2264	Construction inspectors	0.35	0.16	0.49	16,125	0.09%	$63,203.70
2271	Air pilots, flight engineers and flying instructors	0.40	0.10	0.50	17,560	0.09%	$106,763.90
2272	Air traffic controllers and related occupations	0.32	0.21	0.47	4,795	0.03%	$110,331.30
2273	Deck officers, water transport	0.19	0.22	0.59	5,715	0.03%	$87,814.40
2274	Engineer officers, water transport	0.14	0.27	0.59	2,465	0.01%	$89,779.30
2275	Railway traffic controllers and marine traffic regulators	0.22	0.35	0.43	1,570	0.01%	$82,749.60
2281	Computer network technicians	0.66	0.17	0.17	68,250	0.37%	$60,966.60
2282	User support technicians	0.61	0.15	0.24	44,290	0.24%	$53,845.80
2283	Information systems testing technicians	0.28	0.31	0.41	10,020	0.05%	$51,438.40
3011	Nursing co-ordinators and supervisors	0.53	0.17	0.30	16,960	0.09%	$70,227.10
3012	Registered nurses and registered psychiatric nurses	0.83	0.00	0.17	305,740	1.64%	$64,322.60
3111	Specialist physicians	0.83	0.00	0.17	42,210	0.23%	$162,207.80
3112	General practitioners and family physicians	0.37	0.24	0.39	52,335	0.28%	$120,333.90
3113	Dentists	0.78	0.19	0.03	19,110	0.10%	$118,488.00
3114	Veterinarians	0.44	0.15	0.40	9,815	0.05%	$75,594.90
3121	Optometrists	0.46	0.27	0.27	5,245	0.03%	$83,138.10
3122	Chiropractors	0.56	0.20	0.24	7,455	0.04%	$60,707.30
3124	Allied primary health practitioners	0.33	0.01	0.67	7,340	0.04%	$78,627.60
3125	Other professional occupations in health diagnosing and treating	0.46	0.08	0.45	5,630	0.03%	$43,187.60
3131	Pharmacists	0.84	0.20	0.00	37,850	0.20%	$88,130.30
3132	Dietitians and nutritionists	0.71	0.19	0.10	12,045	0.06%	$50,916.30
3141	Audiologists and speech-language pathologists	0.43	0.22	0.35	11,030	0.06%	$61,981.20
3142	Physiotherapists	0.39	0.20	0.41	24,475	0.13%	$58,117.90
3143	Occupational therapists	0.31	0.10	0.58	15,700	0.08%	$58,633.60
3144	Other professional occupations in therapy and assessment	0.31	0.10	0.59	11,330	0.06%	$35,510.00
3211	Medical laboratory technologists	0.28	0.16	0.56	21,045	0.11%	$61,491.30

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
3212	Medical laboratory technicians and pathologists' assistants	0.36	0.00	0.64	23,730	0.13%	$41,609.10
3213	Animal health technologists and veterinary technicians	0.56	0.16	0.29	16,185	0.09%	$29,650.60
3214	Respiratory therapists, clinical perfusionists and cardiopulmonary technologists	0.73	0.10	0.17	11,575	0.06%	$65,286.30
3215	Medical radiation technologists	0.60	0.10	0.30	20,415	0.11%	$62,438.80
3216	Medical sonographers	0.18	0.18	0.64	5,400	0.03%	$64,639.30
3217	Cardiology technologists and electrophysiological diagnostic technologists, n.e.c.	0.43	0.30	0.27	3,065	0.02%	$48,882.50
3219	Other medical technologists and technicians (except dental health)	0.35	0.10	0.56	52,580	0.28%	$31,717.30
3221	Denturists	0.78	0.19	0.03	2,340	0.01%	$57,412.10
3222	Dental hygienists and dental therapists	0.34	0.32	0.34	26,970	0.14%	$49,439.80
3223	Dental technologists, technicians and laboratory assistants	0.21	0.44	0.35	5,785	0.03%	$46,136.90
3231	Opticians	0.39	0.16	0.46	8,905	0.05%	$43,802.30
3232	Practitioners of natural healing	0.42	0.13	0.45	9,165	0.05%	$21,528.80
3233	Licensed practical nurses	0.60	0.13	0.27	73,935	0.40%	$43,884.90
3234	Paramedical occupations	0.67	0.08	0.25	28,585	0.15%	$68,478.90
3236	Massage therapists	0.18	0.30	0.53	33,350	0.18%	$24,454.80
3237	Other technical occupations in therapy and assessment	0.34	0.09	0.57	11,640	0.06%	$35,244.80
3411	Dental assistants	0.48	0.09	0.43	34,750	0.19%	$34,216.90
3413	Nurse aides, orderlies and patient service associates	0.36	0.29	0.35	264,680	1.42%	$31,961.30
3414	Other assisting occupations in support of health services	0.19	0.52	0.29	36,845	0.20%	$33,477.70
4011	University professors and lecturers	0.51	0.53	0.00	73,030	0.39%	$92,882.00
4012	Post-secondary teaching and research assistants	0.60	0.14	0.27	79,555	0.43%	$20,800.40
4021	College and other vocational instructors	0.51	0.53	0.00	96,820	0.52%	$57,357.30
4031	Secondary school teachers	0.36	0.24	0.41	169,965	0.91%	$64,110.10
4032	Elementary school and kindergarten teachers	0.42	0.24	0.34	299,775	1.61%	$58,897.60
4033	Educational counsellors	0.37	0.11	0.52	23,775	0.13%	$54,666.00
4111	Judges	0.22	0.26	0.52	3,320	0.02%	$228,381.20
4112	Lawyers and Quebec notaries	0.17	0.26	0.57	89,990	0.48%	$140,230.30
4151	Psychologists	0.36	0.02	0.62	23,685	0.13%	$59,030.90
4152	Social workers	0.40	0.00	0.60	61,085	0.33%	$56,931.00
4153	Family, marriage and other related counsellors	0.42	0.23	0.35	26,895	0.14%	$46,586.10
4154	Professional occupations in religion	0.44	0.23	0.33	29,895	0.16%	$45,243.10
4155	Probation and parole officers and related occupations	0.38	0.25	0.37	6,065	0.03%	$67,569.40
4156	Employment counsellors	0.37	0.11	0.52	14,500	0.08%	$44,360.10
4161	Natural and applied science policy researchers, consultants and program officers	0.39	0.16	0.45	27,325	0.15%	$73,481.10

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4162	Economists and economic policy researchers and analysts	0.59	0.16	0.25	18,830	0.10%	$94,896.60
4163	Business development officers and marketing researchers and consultants	0.51	0.25	0.24	65,095	0.35%	$65,901.00
4164	Social policy researchers, consultants and program officers	0.46	0.15	0.38	34,255	0.18%	$61,426.80
4165	Health policy researchers, consultants and program officers	0.78	0.04	0.17	33,860	0.18%	$63,409.00
4166	Education policy researchers, consultants and program officers	0.47	0.16	0.38	24,450	0.13%	$57,180.20
4167	Recreation, sports and fitness policy researchers, consultants and program officers	0.66	0.15	0.19	10,940	0.06%	$45,101.70
4168	Program officers unique to government	0.33	0.40	0.27	22,910	0.12%	$49,583.30
4211	Paralegal and related occupations	0.46	0.38	0.16	29,765	0.16%	$48,546.00
4212	Social and community service workers	0.33	0.13	0.53	149,670	0.80%	$38,168.90
4214	Early childhood educators and assistants	0.42	0.34	0.24	206,615	1.11%	$25,098.90
4215	Instructors of persons with disabilities	0.42	0.25	0.33	21,975	0.12%	$38,541.30
4216	Other instructors	0.35	0.36	0.30	30,345	0.16%	$21,071.50
4311	Police officers (except commissioned)	0.41	0.25	0.34	79,400	0.43%	$95,312.20
4312	Firefighters	0.57	0.16	0.27	34,130	0.18%	$90,219.30
4411	Home child care providers	0.46	0.34	0.20	87,070	0.47%	$15,634.80
4412	Home support workers, housekeepers and related occupations	0.36	0.23	0.41	103,925	0.56%	$24,097.10
4413	Elementary and secondary school teacher assistants	0.35	0.32	0.33	131,345	0.71%	$24,210.20
4421	Sheriffs and bailiffs	0.34	0.44	0.22	3,125	0.02%	$54,222.10
4422	Correctional service officers	0.25	0.35	0.40	24,525	0.13%	$68,796.20
4423	By-law enforcement and other regulatory officers, n.e.c.	0.34	0.27	0.39	10,430	0.06%	$57,524.30
5111	Librarians	0.62	0.17	0.21	9,700	0.05%	$58,443.50
5112	Conservators and curators	0.54	0.16	0.30	2,000	0.01%	$48,039.50
5113	Archivists	0.56	0.14	0.30	1,980	0.01%	$46,673.40
5121	Authors and writers	0.43	0.08	0.49	26,750	0.14%	$38,039.30
5122	Editors	0.50	0.13	0.37	17,795	0.10%	$42,307.60
5123	Journalists	0.20	0.37	0.43	12,245	0.07%	$50,552.10
5125	Translators, terminologists and interpreters	0.42	0.38	0.20	17,735	0.10%	$34,325.80
5131	Producers, directors, choreographers and related occupations	0.27	0.26	0.47	26,455	0.14%	$53,794.60
5132	Conductors, composers and arrangers	0.54	0.11	0.35	4,055	0.02%	$28,963.80
5133	Musicians and singers	0.35	0.13	0.52	34,245	0.18%	$18,734.50
5134	Dancers	0.40	0.22	0.37	9,935	0.05%	$16,005.00
5135	Actors and comedians	0.20	0.28	0.52	13,170	0.07%	$19,804.60
5136	Painters, sculptors and other visual artists	0.20	0.16	0.63	19,685	0.11%	$20,091.10
5211	Library and public archive technicians	0.27	0.59	0.14	10,185	0.05%	$37,153.30
5212	Technical occupations related to museums and art galleries	0.48	0.13	0.39	8,670	0.05%	$19,480.30

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5221	Photographers	0.81	0.08	0.11	17,600	0.09%	$20,781.50
5222	Film and video camera operators	0.39	0.16	0.45	5,260	0.03%	$39,909.20
5223	Graphic arts technicians	0.69	0.16	0.16	9,045	0.05%	$45,746.10
5224	Broadcast technicians	0.36	0.28	0.36	2,190	0.01%	$56,846.40
5225	Audio and video recording technicians	0.55	0.18	0.27	13,210	0.07%	$45,784.40
5226	Other technical and co-ordinating occupations in motion pictures, broadcasting and the performing arts	0.37	0.13	0.50	15,225	0.08%	$48,769.40
5227	Support occupations in motion pictures, broadcasting, photography and the performing arts	0.17	0.28	0.55	11,085	0.06%	$38,285.00
5231	Announcers and other broadcasters	0.51	0.18	0.31	6,030	0.03%	$50,735.80
5232	Other performers, n.e.c.	0.12	0.27	0.61	6,625	0.04%	$21,511.50
5241	Graphic designers and illustrators	0.89	0.00	0.11	61,120	0.33%	$39,538.30
5242	Interior designers and interior decorators	0.50	0.18	0.33	24,950	0.13%	$35,832.10
5243	Theatre, fashion, exhibit and other creative designers	0.47	0.21	0.32	14,425	0.08%	$38,304.00
5244	Artisans and craftspersons	0.48	0.13	0.39	14,180	0.08%	$18,950.10
5245	Patternmakers–textile, leather and fur products	0.39	0.14	0.47	1,025	0.01%	$42,446.40
5251	Athletes	0.42	0.26	0.32	2,900	0.02%	$145,583.60
5252	Coaches	0.38	0.19	0.42	10,935	0.06%	$33,581.40
5253	Sports officials and referees	0.37	0.40	0.22	4,825	0.03%	$9,946.70
5254	Program leaders and instructors in recreation, sport and fitness	0.31	0.38	0.31	144,885	0.78%	$13,972.40
6211	Retail sales supervisors	0.41	0.26	0.33	66,435	0.36%	$34,806.10
6221	Technical sales specialists–wholesale trade	0.74	0.09	0.17	78,640	0.42%	$86,444.00
6222	Retail and wholesale buyers	0.47	0.20	0.33	37,445	0.20%	$40,353.50
6231	Insurance agents and brokers	0.30	0.27	0.43	71,485	0.38%	$56,877.50
6232	Real estate agents and salespersons	0.26	0.35	0.39	90,060	0.48%	$50,954.50
6235	Financial sales representatives	0.41	0.15	0.44	63,940	0.34%	$60,354.20
6311	Food service supervisors	0.49	0.22	0.30	43,715	0.23%	$25,426.50
6312	Executive housekeepers	0.41	0.34	0.25	3,960	0.02%	$36,827.90
6313	Accommodation, travel, tourism and related services supervisors	0.43	0.18	0.39	5,110	0.03%	$46,040.80
6314	Customer and information services supervisors	0.42	0.18	0.40	12,075	0.06%	$51,701.90
6315	Cleaning supervisors	0.41	0.34	0.25	11,845	0.06%	$44,275.70
6316	Other services supervisors	0.42	0.18	0.40	15,730	0.08%	$39,117.00
6321	Chefs	0.89	0.00	0.11	62,340	0.33%	$31,127.70
6322	Cooks	0.73	0.00	0.27	238,310	1.28%	$20,488.20
6331	Butchers, meat cutters and fishmongers–retail and wholesale	0.37	0.45	0.18	20,220	0.11%	$30,413.30
6332	Bakers	0.07	0.24	0.70	45,375	0.24%	$23,062.80
6341	Hairstylists and barbers	0.35	0.13	0.53	101,610	0.55%	$19,853.80

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6342	Tailors, dressmakers, furriers and milliners	0.34	0.07	0.59	17,195	0.09%	$20,310.20
6343	Shoe repairers and shoemakers	0.18	0.52	0.30	1,415	0.01%	$23,325.30
6344	Jewellers, jewellery and watch repairers and related occupations	0.34	0.13	0.53	4,900	0.03%	$24,431.40
6345	Upholsterers	0.40	0.12	0.48	5,155	0.03%	$29,797.80
6346	Funeral directors and embalmers	0.33	0.18	0.49	4,900	0.03%	$52,870.30
6411	Sales and account representatives–wholesale trade (non-technical)	0.29	0.16	0.55	113,245	0.61%	$62,138.50
6421	Retail salespersons	0.44	0.09	0.47	720,185	3.87%	$23,752.60
6511	Maîtres d'hôtel and hosts/hostesses	0.43	0.45	0.12	31,550	0.17%	$9,055.70
6512	Bartenders	0.50	0.13	0.37	43,525	0.23%	$17,119.90
6513	Food and beverage servers	0.41	0.40	0.19	246,995	1.33%	$15,076.50
6521	Travel counsellors	0.39	0.09	0.52	25,475	0.14%	$32,171.60
6522	Pursers and flight attendants	0.37	0.17	0.46	16,280	0.09%	$46,571.90
6523	Airline ticket and service agents	0.05	0.70	0.25	13,850	0.07%	$38,176.60
6524	Ground and water transport ticket agents, cargo service representatives and related clerks	0.35	0.38	0.27	3,345	0.02%	$38,175.90
6525	Hotel front desk clerks	0.42	0.12	0.46	23,645	0.13%	$23,399.70
6531	Tour and travel guides	0.52	0.28	0.20	5,855	0.03%	$14,462.80
6532	Outdoor sport and recreational guides	0.39	0.15	0.47	5,010	0.03%	$20,743.80
6533	Casino occupations	0.40	0.47	0.13	13,830	0.07%	$37,505.70
6541	Security guards and related security service occupations	0.44	0.16	0.40	126,810	0.68%	$30,673.70
6551	Customer services representatives–financial institutions	0.32	0.43	0.24	80,740	0.43%	$32,432.20
6552	Other customer and information services representatives	0.32	0.43	0.24	225,805	1.21%	$33,027.10
6561	Image, social and other personal consultants	0.52	0.44	0.04	2,925	0.02%	$26,378.40
6562	Estheticians, electrologists and related occupations	0.43	0.30	0.27	58,910	0.32%	$18,863.70
6563	Pet groomers and animal care workers	0.40	0.13	0.47	24,085	0.13%	$17,505.70
6564	Other personal service occupations	0.42	0.18	0.40	2,390	0.01%	$15,020.10
6611	Cashiers	0.44	0.41	0.15	376,760	2.02%	$12,812.90
6621	Service station attendants	0.17	0.45	0.38	19,575	0.11%	$17,404.20
6622	Store shelf stockers, clerks and order fillers	0.07	0.60	0.33	195,000	1.05%	$18,210.00
6623	Other sales related occupations	0.29	0.09	0.62	44,900	0.24%	$24,952.20
6711	Food counter attendants, kitchen helpers and related support occupations	0.43	0.30	0.27	421,185	2.26%	$13,885.70
6721	Support occupations in accommodation, travel and facilities set-up services	0.44	0.44	0.12	6,130	0.03%	$25,367.10
6722	Operators and attendants in amusement, recreation and sport	0.45	0.27	0.28	38,925	0.21%	$15,816.00
6731	Light duty cleaners	0.73	0.07	0.20	263,430	1.41%	$20,386.40
6732	Specialized cleaners	0.17	0.29	0.54	46,335	0.25%	$25,022.70

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6733	Janitors, caretakers and building superintendents	0.17	0.53	0.31	235,570	1.26%	$32,338.50
6741	Dry cleaning, laundry and related occupations	0.16	0.52	0.32	22,430	0.12%	$25,846.50
6742	Other service support occupations, n.e.c.	0.39	0.33	0.28	31,735	0.17%	$19,470.50
7201	Contractors and supervisors, machining, metal forming, shaping and erecting trades and related occupations	0.31	0.21	0.47	15,490	0.08%	$84,445.70
7202	Contractors and supervisors, electrical trades and telecommunications occupations	0.31	0.21	0.47	17,950	0.10%	$86,217.10
7203	Contractors and supervisors, pipefitting trades	0.31	0.21	0.47	6,425	0.03%	$87,564.90
7204	Contractors and supervisors, carpentry trades	0.31	0.21	0.47	19,365	0.10%	$49,814.30
7205	Contractors and supervisors, other construction trades, installers, repairers and servicers	0.29	0.25	0.46	37,705	0.20%	$52,758.70
7231	Machinists and machining and tooling inspectors	0.24	0.46	0.30	40,080	0.22%	$54,001.20
7232	Tool and die makers	0.13	0.46	0.41	11,820	0.06%	$62,276.60
7233	Sheet metal workers	0.17	0.34	0.48	21,360	0.11%	$55,461.60
7234	Boilermakers	0.24	0.34	0.42	4,525	0.02%	$79,363.70
7235	Structural metal and platework fabricators and fitters	0.17	0.54	0.30	6,120	0.03%	$53,576.80
7236	Ironworkers	0.17	0.34	0.50	15,490	0.08%	$65,592.30
7237	Welders and related machine operators	0.21	0.54	0.25	99,160	0.53%	$52,107.30
7241	Electricians (except industrial and power system)	0.40	0.11	0.49	97,205	0.52%	$56,454.50
7242	Industrial electricians	0.24	0.23	0.54	30,715	0.16%	$86,846.30
7243	Power system electricians	0.40	0.11	0.49	6,495	0.03%	$88,852.00
7244	Electrical power line and cable workers	0.36	0.27	0.38	13,190	0.07%	$95,371.70
7245	Telecommunications line and cable workers	0.20	0.52	0.27	10,845	0.06%	$56,862.30
7246	Telecommunications installation and repair workers	0.53	0.13	0.34	27,810	0.15%	$58,523.70
7247	Cable television service and maintenance technicians	0.63	0.14	0.24	1,890	0.01%	$47,357.60
7251	Plumbers	0.26	0.16	0.59	53,140	0.29%	$53,106.90
7252	Steamfitters, pipefitters and sprinkler system installers	0.30	0.13	0.57	24,120	0.13%	$72,086.60
7253	Gas fitters	0.32	0.13	0.55	7,445	0.04%	$57,093.60
7271	Carpenters	0.45	0.20	0.35	166,925	0.90%	$39,622.10
7272	Cabinetmakers	0.45	0.20	0.35	18,840	0.10%	$32,867.40
7281	Bricklayers	0.17	0.43	0.40	19,355	0.10%	$39,572.50
7282	Concrete finishers	0.21	0.57	0.22	12,125	0.07%	$47,526.40
7283	Tilesetters	0.37	0.13	0.51	10,145	0.05%	$32,310.60
7284	Plasterers, drywall installers and finishers and lathers	0.32	0.13	0.55	29,375	0.16%	$35,301.20
7291	Roofers and shinglers	0.17	0.57	0.26	23,025	0.12%	$35,046.60
7292	Glaziers	0.17	0.56	0.27	10,085	0.05%	$44,957.30
7293	Insulators	0.31	0.57	0.12	11,245	0.06%	$56,651.20
7294	Painters and decorators (except interior decorators)	0.16	0.11	0.74	48,205	0.26%	$27,047.00

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
7295	Floor covering installers	0.19	0.52	0.28	15,440	0.08%	$31,144.50
7301	Contractors and supervisors, mechanic trades	0.35	0.15	0.50	23,555	0.13%	$73,698.20
7302	Contractors and supervisors, heavy equipment operator crews	0.31	0.21	0.47	39,005	0.21%	$78,347.20
7303	Supervisors, printing and related occupations	0.37	0.25	0.38	3,025	0.02%	$56,441.80
7304	Supervisors, railway transport operations	0.37	0.20	0.43	2,105	0.01%	$91,712.40
7305	Supervisors, motor transport and other ground transit operators	0.39	0.37	0.25	9,280	0.05%	$68,430.20
7311	Construction millwrights and industrial mechanics	0.50	0.28	0.22	76,030	0.41%	$73,471.40
7312	Heavy-duty equipment mechanics	0.24	0.00	0.76	40,720	0.22%	$73,164.20
7313	Heating, refrigeration and air conditioning mechanics	0.46	0.26	0.28	25,970	0.14%	$59,033.10
7314	Railway carmen/women	0.43	0.34	0.23	2,720	0.01%	$70,497.30
7315	Aircraft mechanics and aircraft inspectors	0.53	0.16	0.31	17,615	0.09%	$69,408.30
7316	Machine fitters	0.24	0.46	0.30	2,510	0.01%	$58,852.30
7318	Elevator constructors and mechanics	0.45	0.10	0.45	5,415	0.03%	$93,788.60
7321	Automotive service technicians, truck and bus mechanics and mechanical repairers	0.44	0.13	0.43	156,845	0.84%	$48,294.90
7322	Motor vehicle body repairers	0.37	0.57	0.06	29,605	0.16%	$47,238.30
7331	Oil and solid fuel heating mechanics	0.51	0.16	0.33	2,735	0.01%	$43,325.70
7332	Appliance servicers and repairers	0.45	0.16	0.39	7,370	0.04%	$39,124.20
7333	Electrical mechanics	0.59	0.15	0.26	9,810	0.05%	$56,370.40
7334	Motorcycle, all-terrain vehicle and other related mechanics	0.52	0.32	0.16	5,890	0.03%	$44,100.90
7335	Other small engine and small equipment repairers	0.19	0.24	0.57	3,240	0.02%	$34,749.90
7361	Railway and yard locomotive engineers	0.23	0.35	0.43	4,860	0.03%	$101,576.70
7362	Railway conductors and brakemen/women	0.22	0.35	0.43	5,285	0.03%	$78,956.70
7371	Crane operators	0.18	0.51	0.31	15,690	0.08%	$77,052.80
7372	Drillers and blasters–surface mining, quarrying and construction	0.07	0.34	0.59	2,700	0.01%	$64,375.40
7373	Water well drillers	0.07	0.34	0.59	855	0.00%	$55,083.50
7381	Printing press operators	0.21	0.20	0.60	17,250	0.09%	$44,724.30
7384	Other trades and related occupations, n.e.c.	0.26	0.52	0.21	12,865	0.07%	$46,643.40
7441	Residential and commercial installers and servicers	0.42	0.09	0.49	50,165	0.27%	$33,669.50
7442	Waterworks and gas maintenance workers	0.06	0.77	0.17	5,475	0.03%	$66,554.50
7444	Pest controllers and fumigators	0.14	0.19	0.67	4,180	0.02%	$37,723.80
7451	Longshore workers	0.17	0.51	0.32	7,275	0.04%	$72,536.00
7452	Material handlers	0.29	0.52	0.19	195,350	1.05%	$34,436.50
7511	Transport truck drivers	0.29	0.37	0.35	319,720	1.72%	$45,137.60
7512	Bus drivers, subway operators and other transit operators	0.39	0.30	0.32	97,270	0.52%	$38,173.80
7513	Taxi and limousine drivers and chauffeurs	0.41	0.56	0.04	58,795	0.32%	$17,313.40
7514	Delivery and courier service drivers	0.27	0.27	0.47	95,515	0.51%	$29,558.50

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
7521	Heavy equipment operators (except crane)	0.17	0.57	0.26	96,895	0.52%	$62,016.70
7522	Public works maintenance equipment operators and related workers	0.22	0.43	0.35	26,920	0.14%	$45,255.50
7531	Railway yard and track maintenance workers	0.10	0.57	0.33	6,460	0.03%	$68,452.10
7532	Water transport deck and engine room crew	0.34	0.37	0.29	4,825	0.03%	$52,846.40
7533	Boat and cable ferry operators and related occupations	0.19	0.22	0.59	2,745	0.01%	$45,536.90
7534	Air transport ramp attendants	0.30	0.45	0.25	10,510	0.06%	$35,780.30
7535	Other automotive mechanical installers and servicers	0.20	0.25	0.54	18,390	0.10%	$36,017.80
7611	Construction trades helpers and labourers	0.09	0.57	0.34	206,465	1.11%	$36,163.60
7612	Other trades helpers and labourers	0.26	0.52	0.22	10,595	0.06%	$35,237.70
7621	Public works and maintenance labourers	0.33	0.57	0.10	34,540	0.19%	$38,441.20
7622	Railway and motor transport labourers	0.15	0.53	0.32	5,305	0.03%	$35,124.30
8211	Supervisors, logging and forestry	0.83	0.28	0.00	4,600	0.02%	$59,283.50
8221	Supervisors, mining and quarrying	0.31	0.21	0.47	7,065	0.04%	$121,630.60
8222	Contractors and supervisors, oil and gas drilling and services	0.31	0.21	0.47	15,165	0.08%	$124,417.20
8231	Underground production and development miners	0.17	0.58	0.25	16,555	0.09%	$95,788.50
8232	Oil and gas well drillers, servicers, testers and related workers	0.05	0.76	0.19	11,895	0.06%	$85,339.80
8241	Logging machinery operators	0.13	0.48	0.39	8,695	0.05%	$56,468.80
8252	Agricultural service contractors, farm supervisors and specialized livestock workers	0.84	0.48	0.00	10,270	0.06%	$35,374.60
8255	Contractors and supervisors, landscaping, grounds maintenance and horticulture services	0.17	0.38	0.46	21,240	0.11%	$37,821.30
8261	Fishing masters and officers	0.00	0.89	0.11	2,990	0.02%	$65,719.60
8262	Fishermen/women	0.00	0.91	0.09	22,420	0.12%	$38,374.70
8411	Underground mine service and support workers	0.13	0.58	0.29	3,325	0.02%	$73,089.00
8412	Oil and gas well drilling and related workers and services operators	0.13	0.51	0.36	8,955	0.05%	$84,608.40
8421	Chain saw and skidder operators	0.11	0.52	0.37	8,565	0.05%	$33,318.10
8422	Silviculture and forestry workers	0.34	0.16	0.51	8,320	0.04%	$28,427.40
8431	General farm workers	0.05	0.52	0.43	103,555	0.56%	$22,520.20
8432	Nursery and greenhouse workers	0.11	0.52	0.37	16,920	0.09%	$16,678.10
8441	Fishing vessel deckhands	0.00	0.89	0.11	6,570	0.04%	$30,120.20
8442	Trappers and hunters	0.13	0.57	0.30	715	0.00%	$13,908.80
8611	Harvesting labourers	0.12	0.51	0.37	8,100	0.04%	$15,683.20
8612	Landscaping and grounds maintenance labourers	0.12	0.36	0.53	122,030	0.66%	$19,997.40
8613	Aquaculture and marine harvest labourers	0.29	0.28	0.43	2,435	0.01%	$23,345.50
8614	Mine labourers	0.13	0.58	0.29	3,805	0.02%	$57,705.80
8615	Oil and gas drilling, servicing and related labourers	0.08	0.58	0.35	11,005	0.06%	$59,301.20

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
9211	Supervisors, mineral and metal processing	0.37	0.25	0.38	8,140	0.04%	$78,115.30
9212	Supervisors, petroleum, gas and chemical processing and utilities	0.36	0.26	0.38	15,000	0.08%	$104,036.90
9213	Supervisors, food and beverage processing	0.37	0.25	0.38	13,565	0.07%	$53,819.50
9214	Supervisors, plastic and rubber products manufacturing	0.37	0.25	0.38	5,570	0.03%	$61,167.70
9215	Supervisors, forest products processing	0.37	0.25	0.38	6,800	0.04%	$77,541.20
9217	Supervisors, textile, fabric, fur and leather products processing and manufacturing	0.37	0.25	0.38	1,955	0.01%	$43,637.10
9221	Supervisors, motor vehicle assembling	0.37	0.25	0.38	8,160	0.04%	$78,780.20
9222	Supervisors, electronics manufacturing	0.37	0.25	0.38	1,770	0.01%	$62,844.10
9223	Supervisors, electrical products manufacturing	0.37	0.25	0.38	1,325	0.01%	$67,197.70
9224	Supervisors, furniture and fixtures manufacturing	0.37	0.25	0.38	2,915	0.02%	$50,702.90
9226	Supervisors, other mechanical and metal products manufacturing	0.37	0.25	0.38	4,060	0.02%	$71,709.20
9227	Supervisors, other products manufacturing and assembly	0.37	0.25	0.38	3,905	0.02%	$56,584.30
9231	Central control and process operators, mineral and metal processing	0.09	0.53	0.38	2,155	0.01%	$86,018.70
9232	Central control and process operators, petroleum, gas and chemical processing	0.00	0.67	0.33	19,130	0.10%	$113,716.50
9235	Pulping, papermaking and coating control operators	0.09	0.57	0.35	2,910	0.02%	$68,890.10
9241	Power engineers and power systems operators	0.15	0.57	0.28	31,075	0.17%	$102,748.80
9243	Water and waste treatment plant operators	0.12	0.49	0.39	13,180	0.07%	$60,087.10
9411	Machine operators, mineral and metal processing	0.09	0.53	0.38	10,490	0.06%	$67,955.70
9412	Foundry workers	0.21	0.52	0.27	4,035	0.02%	$51,188.90
9413	Glass forming and finishing machine operators and glass cutters	0.05	0.79	0.16	3,550	0.02%	$34,404.00
9414	Concrete, clay and stone forming operators	0.21	0.57	0.22	6,315	0.03%	$41,411.80
9415	Inspectors and testers, mineral and metal processing	0.07	0.89	0.05	2,815	0.02%	$52,233.30
9416	Metalworking and forging machine operators	0.07	0.79	0.15	15,995	0.09%	$44,170.10
9417	Machining tool operators	0.45	0.33	0.22	11,540	0.06%	$45,379.80
9418	Other metal products machine operators	0.05	0.75	0.20	7,915	0.04%	$42,860.80
9421	Chemical plant machine operators	0.27	0.70	0.02	10,385	0.06%	$48,262.50
9422	Plastics processing machine operators	0.07	0.80	0.13	18,385	0.10%	$40,159.10
9423	Rubber processing machine operators and related workers	0.21	0.57	0.22	8,120	0.04%	$48,067.00
9431	Sawmill machine operators	0.20	0.47	0.33	9,005	0.05%	$45,493.60
9432	Pulp mill machine operators	0.10	0.77	0.13	2,440	0.01%	$73,871.10
9433	Papermaking and finishing machine operators	0.16	0.57	0.28	3,440	0.02%	$58,640.60
9434	Other wood processing machine operators	0.20	0.46	0.34	5,635	0.03%	$45,528.00
9435	Paper converting machine operators	0.16	0.57	0.28	5,195	0.03%	$45,778.30

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
9436	Lumber graders and other wood processing inspectors and graders	0.34	0.30	0.37	3,400	0.02%	$47,033.10
9437	Woodworking machine operators	0.21	0.57	0.23	7,385	0.04%	$34,184.50
9441	Textile fibre and yarn, hide and pelt processing machine operators and workers	0.10	0.71	0.19	4,130	0.02%	$31,386.60
9442	Weavers, knitters and other fabric making occupations	0.28	0.51	0.21	3,695	0.02%	$26,203.30
9445	Fabric, fur and leather cutters	0.10	0.71	0.19	1,860	0.01%	$26,007.60
9446	Industrial sewing machine operators	0.20	0.47	0.33	17,825	0.10%	$22,271.20
9447	Inspectors and graders, textile, fabric, fur and leather products manufacturing	0.07	0.89	0.05	2,270	0.01%	$30,299.90
9461	Process control and machine operators, food and beverage processing	0.13	0.54	0.34	35,865	0.19%	$40,837.00
9462	Industrial butchers and meat cutters, poultry preparers and related workers	0.37	0.45	0.18	15,260	0.08%	$34,040.40
9463	Fish and seafood plant workers	0.09	0.52	0.39	7,795	0.04%	$18,261.60
9465	Testers and graders, food and beverage processing	0.07	0.89	0.05	5,305	0.03%	$35,297.70
9471	Plateless printing equipment operators	0.22	0.54	0.24	7,660	0.04%	$37,100.60
9472	Camera, platemaking and other prepress occupations	0.49	0.14	0.38	2,825	0.02%	$46,127.30
9473	Binding and finishing machine operators	0.47	0.36	0.17	5,210	0.03%	$32,700.70
9474	Photographic and film processors	0.49	0.40	0.11	2,570	0.01%	$26,734.90
9521	Aircraft assemblers and aircraft assembly inspectors	0.21	0.34	0.45	7,075	0.04%	$63,391.70
9522	Motor vehicle assemblers, inspectors and testers	0.05	0.77	0.18	68,855	0.37%	$47,191.10
9523	Electronics assemblers, fabricators, inspectors and testers	0.07	0.77	0.17	16,065	0.09%	$35,676.00
9524	Assemblers and inspectors, electrical appliance, apparatus and equipment manufacturing	0.21	0.57	0.23	8,660	0.05%	$39,453.20
9525	Assemblers, fabricators and inspectors, industrial electrical motors and transformers	0.07	0.77	0.17	2,225	0.01%	$44,875.20
9526	Mechanical assemblers and inspectors	0.05	0.77	0.18	11,800	0.06%	$44,540.70
9527	Machine operators and inspectors, electrical apparatus manufacturing	0.07	0.89	0.05	2,015	0.01%	$40,347.80
9531	Boat assemblers and inspectors	0.16	0.51	0.33	1,630	0.01%	$37,646.00
9532	Furniture and fixture assemblers and inspectors	0.07	0.88	0.05	12,080	0.06%	$30,144.00
9534	Furniture finishers and refinishers	0.37	0.29	0.34	6,765	0.04%	$31,194.70
9535	Plastic products assemblers, finishers and inspectors	0.07	0.89	0.05	12,050	0.06%	$33,851.10
9536	Industrial painters, coaters and metal finishing process operators	0.20	0.46	0.34	17,865	0.10%	$45,971.90
9537	Other products assemblers, finishers and inspectors	0.07	0.40	0.53	24,740	0.13%	$32,814.10
9611	Labourers in mineral and metal processing	0.19	0.52	0.29	10,175	0.05%	$42,809.10
9612	Labourers in metal fabrication	0.19	0.52	0.29	15,855	0.09%	$36,667.40
9613	Labourers in chemical products processing and utilities	0.19	0.52	0.29	10,005	0.05%	$39,185.30

NOC	Occupation	Predicted portion of experts who project growth	Predicted portion of experts who project decline	Implied portion of experts who project no change	Employment	% of Canadian employment	Average income
9614	Labourers in wood, pulp and paper processing	0.19	0.52	0.29	24,745	0.13%	$37,130.50
9615	Labourers in rubber and plastic products manufacturing	0.19	0.52	0.29	8,995	0.05%	$29,864.30
9616	Labourers in textile processing	0.19	0.33	0.48	3,870	0.02%	$24,958.90
9617	Labourers in food and beverage processing	0.19	0.52	0.29	81,380	0.44%	$27,216.90
9618	Labourers in fish and seafood processing	0.19	0.52	0.29	13,410	0.07%	$15,551.10
9619	Other labourers in processing, manufacturing and utilities	0.21	0.57	0.23	90,410	0.49%	$25,887.70

All employment information is sourced from Statistics Canada's enumeration of workers with income in the 2016 Census.

ENDNOTES

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64. For more information on the survey collected, see Appendix A: Workshop Details.

65. The Canadian National Occupational Classification (NOC) taxonomy outlines 500 different occupations.

66. The occupation selection process is detailed in Appendix A: Occupation Selection.

67. Relative regional dependence is a ratio of the regional employment share over the national employment share of a given occupation. When an occupation presents a high ratio in a region, it suggests that geography is relatively more dependent on the occupation for employment than the country as a whole.

68. For more details on the other questions included in the expert survey, please see Appendix A: Workshop Details.

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79. "Sex and Gender." Statistics Canada. February 18, 2019. https://www12.statcan.gc.ca/census-recensement/2021/road2021-chemin2021/fs-fi/sex-and-gender.cfm.

80. An average of predicted portions for 4-digit National Occupation Codes, weighted by national employment.

81. Industry NAICS codes 62, 54, and 72.

82. Minor occupational groups as defined by the National Occupational Classification, which are 3-digit codes. BII+E's model generates predictions for each occupation at the 4-digit level, provided in the Appendix. However, the results below aim to provide more context by presenting estimates at a higher level.

83. This percentage indicates the likelihood of an occupation to be classified as increasing by workshop experts.

84. Lamb, Creig. *The Talented Mr. Robot: The Impact of Automation on Canada's Workforce*. Brookfield Institute for Innovation + Entrepreneurship. June 2016. https://brookfieldinstitute.ca/wp-content/uploads/TalentedMrRobot_BIIE-1.pdf.

85. Minor occupational groups as defined by the National Occupational Classification, which are 3-digit codes.

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90. There are only 292 COPS occupational groupings. ESDC combines NOC codes if their employment numbers are lower than 10,000. This study averages projections over these same groupings to make comparisons possible.

91. See Appendix A: Expert survey data for more details on the training data collected.

92. "Other services" includes equipment and machinery repairing, promoting or administering religious activities, grantmaking, advocacy, laundry services, etc.

93. 93See Methodology: Identifying skills for 2030 for more detail.

94. Deming, David J. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics.* 132: 4. November 2017.

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96. Vu, Viet, Creig Lamb, and Rob Willoughby. *I, Human: Digital and Soft Skills in a New Economy*. Brookfield Institute for Innovation + Entrepreneurship. December 2019. https://brookfieldinstitute.ca/wp-content/uploads/I-Human-ONLINE-FA.pdf.

97. For all foundational traits, the most common importance threshold is 2.5.

98. The worker attributes presented here had a positive influence in over 90% of instances, across multiple runs of the model.

99. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

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104. 70% of occupations are below the model's importance score requirements for this ability and 30% are above the typical threshold of 2.5. See methodology for details.

105. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

106. 60% of the thresholds are the typical 2.5, but 40% are 3.5. See Methodology for details.

107. 73% of occupations meet the 2.5, normal threshold, while only 16% meet the high threshold of 3.5. See Methodology for more information.

108. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

109. The threshold used here is 2.5, see the methodology for details

110. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

111. The threshold used here is 2.5, see Methodology for details.

112. The only exception is trades transport and equipment operators whose workers seem to have a more varied distribution.

113. See Methodology and Appendix C for details.

114. Vu, Viet, Creig Lamb, and Rob Willoughby. *I, Human: Digital and Soft Skills in a New Economy*. Brookfield Institute for Innovation + Entrepreneurship. December 2019. https://brookfieldinstitute.ca/wp-content/uploads/I-Human-ONLINE-FA.pdf.

115. See Appendix B: Feature Importance for more details.

116. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

117. When Chemistry is considered in a decision node, a high score leads to a higher growth projection 84% of instances. Most decision thresholds are 2.5, although 25% are less (2 and 1.5). See Methodology for more details.

118. "The O*NET® Content Model at O*NET Resource Center," O*NET Resource Center, accessed October 21, 2019, https://www.onetcenter.org/content.html.

119. When Computer and Electronics is considered in a decision node, a high score leads to a higher growth projection 74% of instances.

120. Most thresholds are 3.5. See Methodology for details.

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123. "The O*NET® Content Model at O*NET Resource Center." O*NET Resource Center. https://www.onetcenter.org/content.html.

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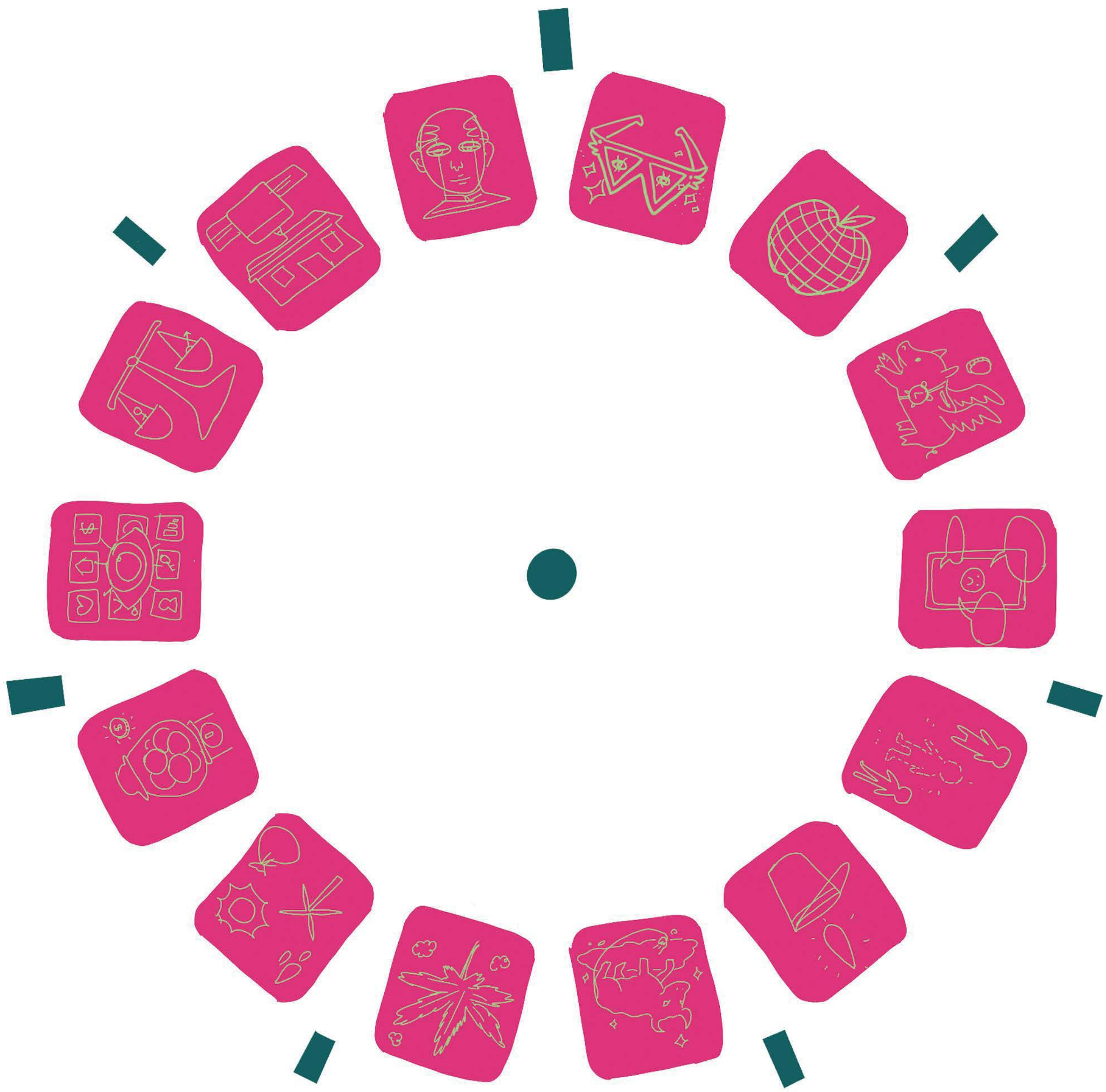

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