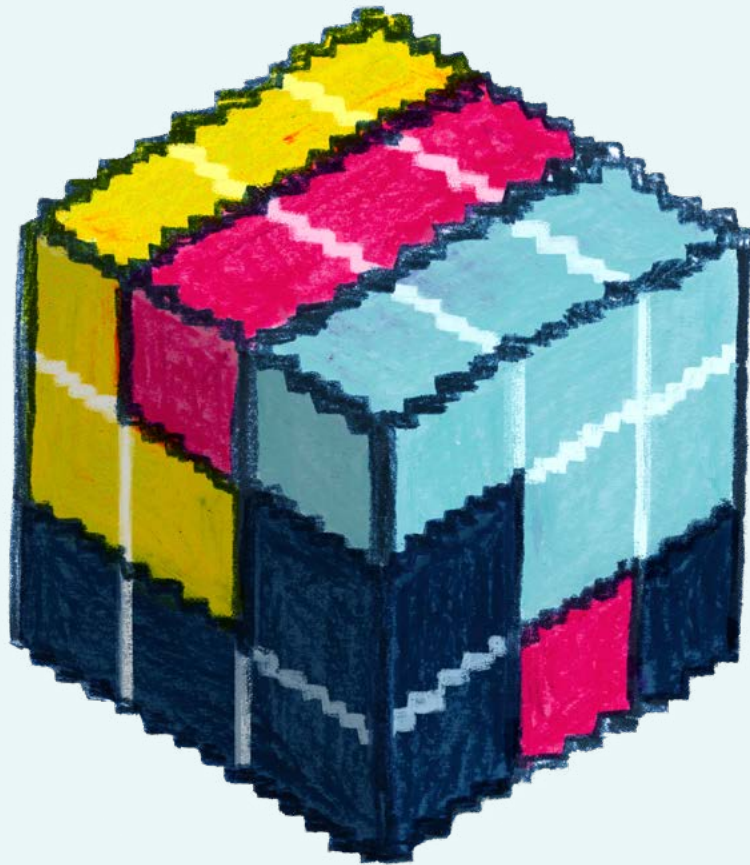


I, Human:

Digital and soft skills in a
new economy

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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.

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Burning Glass Technologies delivers job market analytics that empower employers, workers, and educators to make data-driven decisions. The company's artificial intelligence technology analyzes hundreds of millions of job postings and real-life career transitions to provide insight into labor market patterns. This real-time strategic intelligence offers crucial insights, such as which jobs are most in demand, the specific skills employers need, and the career directions that offer the highest potential for workers. Find out more at www.burning-glass.com/



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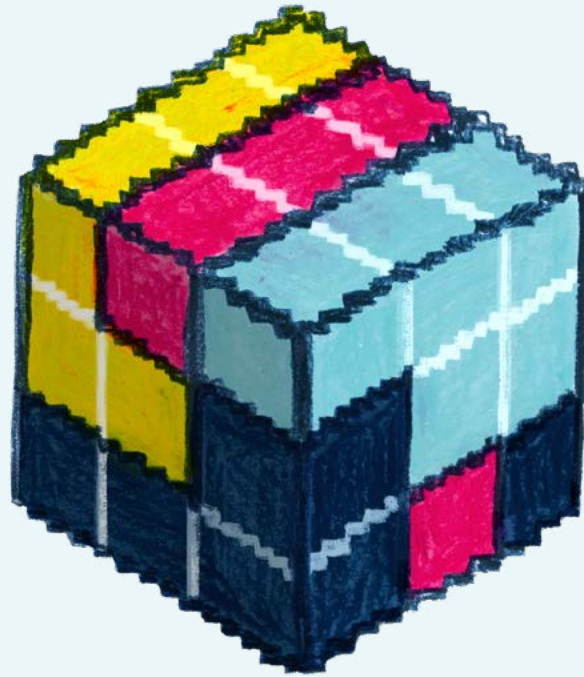


TABLE OF CONTENTS

Executive Summary	1	Hybrid Job Trends: Combining digital and non-digital skills	25
Digital skills	2	Overview	25
Four Hybrid Job Trends: Combining digital and non-digital skills	3	Canadians, across jobs and industries, could benefit from a basket of skills that includes baseline digital skills and complementary soft skills	26
Introduction	6	In highly technical roles, strong digital skills are necessary — but not at the expense of strong soft skills	29
Background and Context	7	Digitization of communications, art, and design	33
Methodology	8	Conclusion and Discussion	41
Data Overview	8	The demand for digital and non-digital skills	41
Defining Digital Skills	11	Appendix A: Overview and Representativeness of the Data	43
The Anatomy of Digital Skills Demands in Canada	13	Appendix B: Definition of Digital Skills	55
Summary	13	Appendix C: Network Analytical Framework	62
The Digital Skills Spectrum	15	Appendix D: Non-digital Skills Clusters	66
The Digital Skills Employers Ask for the Most	15		
Digital Skills Framework	16		
Workforce Digital Skills	17		
Data Skills	19		
System Infrastructure Skills	21		
Software / Product Development Skills	23		



EXECUTIVE SUMMARY



To illuminate the different combinations of skills that Canadians need to be competitive in the labour market, we have partnered with Burning Glass Technologies (Burning Glass) to examine job posting data from January 2012 to December 2018. This data covers all of the English-language online job postings in Canada, and reflects the combination of skills that employers believe a candidate needs, providing a proxy for current skill demands in the labour market.

Using this data, we first sought to uncover the demand for digital skills in Canada. We propose a new robust measure of digital skills, allowing us to place digital skills on a continuum based on their relative digital intensity. Second, we identified a number of distinct clusters of digital skills, then

examined how these clusters interact and appear together with similarly clustered non-digital skills. Finally, using these insights, we uncovered trends where employers are looking for distinct combinations of digital and non-digital skills — resulting in what we are calling hybrid jobs.

The purpose of this report is to analyze which skills are most in-demand, and how skills from different domains go together, so job seekers can understand how to build on their existing skill sets to enhance their competitiveness in the labour market.

DIGITAL SKILLS

From previous Brookfield Institute studies,¹ we know that digital skills vary and exist on a continuum. However, there is a lack of clarity around where specific skills are placed in that continuum, how they interact, and what combinations of digital skills Canadian employers are looking for in specific areas of the economy.

In this report, we place all 13,000 skills in the dataset along a continuum based on their digital intensity, defined by the frequency with which a skill appears in digitally-intensive occupations. For this report, we use “skills” as a catch-all for skills, abilities, knowledge, and other elements required for workers to be successful in a job. Within the broad category of skills that we define as digital, there is substantial variation in each skill’s digital intensity, the application of these skills, and the knowledge, expertise, and training required.

At one end of the spectrum are the skills that show up frequently in job postings attached to the most digitally-intensive occupations. These include highly technical digital skills and knowledge such as data vault modeling, knowledge of clustering algorithms, and programming languages such as Python. The digital skills attached to less digitally-

intensive occupations include, for example, the ability to use web-based project management software, Microsoft Office, and accounting software.

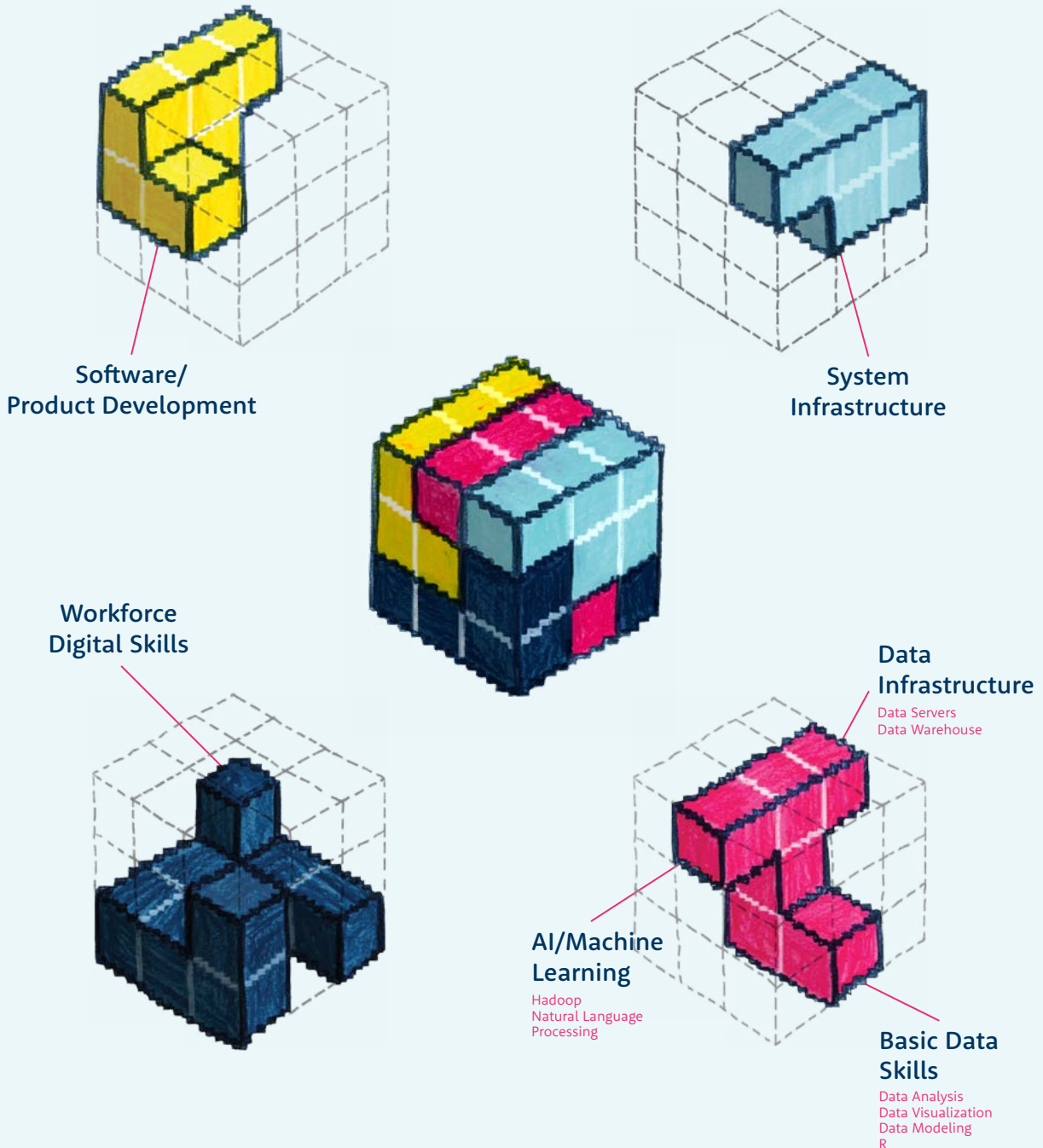
The most in-demand digital skills across the Canadian economy are not highly technical programming languages, but everyday digital skills, in particular those associated with using the Microsoft Office Suite. However, employers are also looking for much more digitally-intensive skills that relate to data, including SQL and SAP, indicating the importance of data analysis skills in today’s economy. Canada’s growing tech and digital economy is also reflected in the number of times employers ask for general software skills, as well as specific programming languages such as Java.

Table A: Top 10 Digital Skills by Number of Job Postings That Mention Them

Skill	Description	Number of mentions	Digital intensity classification
<i>Microsoft Excel</i>	Spreadsheet software	741,191	Low
<i>Microsoft Office</i>	Work productivity software suite	621,690	Low
<i>Microsoft Word</i>	Document composing software	296,992	Low
<i>Microsoft PowerPoint</i>	Presentation creation software	266,748	Low
<i>SQL</i>	Database management software	163,000	High
<i>Spreadsheets</i>	Data organization	151,719	Low
<i>Software Development</i>	General skill	133,681	High
<i>Technical Support</i>	General skill	130,540	Medium
<i>SAP</i>	Business enterprise software	126,787	Medium
<i>Java</i>	Programming language	112,680	High

In our definition of digital skills, four distinct clusters of skills have emerged. First are the less digitally-intensive, general workforce digital skills, which are the most requested and most pervasive across the economy. Second are data skills that also appear across a variety of occupational and industrial contexts. These skills vary from baseline data skills applicable across the economy to more specialized, digitally-intensive data skills, such as the skills associated with machine learning

and other data science techniques. The last two clusters are the most digitally-intensive: system infrastructure, which includes skills ranging from setting up and managing cloud computing services to more general IT support, and software and product development, which includes skills pertaining to the generation of new digital products, both web- and software-based.



FOUR HYBRID JOB TRENDS: COMBINING DIGITAL AND NON- DIGITAL SKILLS

Four major hybrid job trends emerged in the data, where employers are looking for distinct combinations of digital and non-digital skills.

Canadians across the economy require a 21st-century toolkit that includes general workforce digital skills and a suite of soft skills

Despite a growing narrative around the importance of learning to code, for most Canadians, foundational digital skills alongside a suite of non-digital skills — in particular, interpersonal skills — are critical foundations to be competitive in the labour market.

General workforce digital skills, while less digitally-intensive, show up in roughly one third of all job postings in Canada. This includes the baseline digital skills that most Canadian workers need, the most predominant of which are those found in the Microsoft Office Suite. It also includes occupation-specific software, such as business intelligence software and SAS.

The most common skills appearing alongside workforce digital skills are communication and organizational skills. Other soft skills likely to appear alongside workforce digital skills include interpersonal skills, such as ‘teamwork’, ‘collaboration’, and ‘customer service’; project management skills, such as ‘budgeting’ and ‘planning’; and more general skills and aptitudes, such as ‘problem-solving’ and ‘detail-orientedness’.

For highly technical workers, digital skills are necessary, but must be augmented by non-digital skills

Roles requiring a high proportion of skills from the Software/Product Development and Systems Infrastructure skills clusters are not only the most digitally-intensive, but also the most hybrid. This means that in addition to digital skills, employers

ask for non-digital skills from different domains at a higher intensity compared to other roles.

For these highly-digital roles, employers are looking for particularly dynamic candidates, with technical domain knowledge augmented by many non-digital skills; The most frequently requested of which are communications, teamwork, problem solving, and project management, reflecting the creative and collaborative nature of these roles.

For current and prospective workers in these fields, strong digital skills are necessary, but insufficient. It is perhaps just as critical to enhance one’s interpersonal, creative, and problem-solving skills and abilities.

For many creative professionals, design-oriented digital skills are essential

In many core creative roles, from advertising professionals to video game designers, employers are looking for candidates with a strong overlap in non-digital communications, marketing, and/or design skills, as well as design-oriented digital tools, such as Adobe Photoshop and CSS.

The digital skills that are in-demand for these creative professionals pertain to graphic design, web development, and marketing/communications. For these workers, the tools from the Adobe Creative Suite are requested most often. Many of these jobs also require digital skills that relate to marketing and communications — the ability to use social media platforms were among the most commonly requested. Digital marketing management tools and general web development skills are also in high demand. From an employer perspective, the core creative practices, which include non-digital communications, marketing, and design skills, remain the most important elements of the job; but, in many cases, these must be augmented by specific digital skills and abilities.

Data skills are highly in-demand and act as connectors between less and more digitally-intensive occupations

Data is becoming an indispensable component of our economy. **For workers, data skills are not only some of the most in-demand digital skills, but can also serve as a link between less and more digitally-intensive roles.**

One area of upgrading that offers promise is advancement from Microsoft Excel to SQL. Microsoft Excel is the single most in-demand

digital skill in Canada, and as a spreadsheet program is applicable across the economy. SQL, a database querying software, is much more digitally-intensive, but is also the fifth most requested digital skill in Canada. While these skills sit within two distinct clusters, with different levels of digital intensity, they also form a strong connection with one another. There are many instances in which an employer asks for both Excel and SQL in the same job posting. An individual who is proficient at Excel and seeking to become more competitive in digitally-intensive roles may consider learning SQL. However, these kinds of job transitions will also likely require skill and credential upgrading in other areas.

In recent years, the rate with which new technologies emerge and shape the career landscape appears to be accelerating. New job titles such as “AI Ethicist”, “Machine Learning Consultant”, and “Social Media Ninja” pop up seemingly every day. Many of these jobs straddle skills from different domains. This can make it difficult for workers to keep up with employer demands in the labour market.

To help make sense of the changing demand for skills, research from academia, governments, and the private sector has emphasized how technological and societal change, such as automation and population aging, are changing the landscape of skills and work. Collectively, these studies conclude that workers are expected to possess a suite of skills from many domains simultaneously, including digital literacy, interpersonal and communications skills, as well as judgment, problem-solving, and creativity.

In response, concerted efforts are being taken across Canada to help workers gain the skills that will make them more successful and resilient in a changing economy. This includes significant investments in coding and digital literacy education, as well as a growing interest in the development of corresponding non-digital skills, often referred to as ‘soft skills’.

However, these skill sets are often described in general terms, and little is known about the current

— let alone the future — landscape of employer demand for specific combinations of skills. This lack of visibility into skills demands inhibits policy makers and educators from effectively responding to changing skills demands, and workers from developing the right set of skills that will help them succeed in the job market and their career.

This report uses job postings data from Burning Glass Technologies (Burning Glass) to help define digital skills and uncover the demand for digital and non-digital skills. This research is designed to help guide the efforts of policymakers, educators, and training organizations focused on skills development for the future of work, as well as helping students and job seekers looking to understand what skill combinations are likely to serve them best in the job market.

The rest of the report is structured as follows:

1. **Background and context**
2. **Methodology**
3. **The Anatomy of Digital Skills Demand**
4. **Digital Skills Clusters**
5. **Hybrid job trends: combining digital and non-digital skills**

BACKGROUND AND CONTEXT

Across most advanced economies, technological change, globalization, and demographic trends, to name a few, have contributed to a decline in the demand for routine, predictable work, while increasing the need for non-routine job tasks, both high- and low-skilled.² To stay abreast of these changes, Canadians are increasingly expected to be equipped with a variety of skills from different domains at once — which often includes a mix of digital and complementary non-digital skills.

In the US, between 2002 and 2016, the share of employment in occupations with high digital content grew from 4.8 to 23 percent of employment, largely driven by increasing digital skills demand amongst existing jobs.³ While programming and coding are certainly an integral component, digital skills exist on a spectrum. They range from the digital skills all workers need to perform in a modern workplace, such as those associated with composing a document in Microsoft Word, to more advanced digital skills associated with developing and testing new technologies, such as deploying big data analytics infrastructure in Hadoop.⁴

As demand for digital skills increases, so does the need for non-digital skills, such as social and emotional skills, judgment, problem-solving, and creativity. One study showed that while 40 percent of US high-tech companies offshore many job tasks, those that require a high degree of interpersonal interaction remain in the country.⁵ Similarly, from 1880 to 2000 in the US, improvements in technology led to an increase in the employment share for work involving a high degree of communication and human interaction.⁶

Other research has shown that as new waves of automation technologies, such as machine learning algorithms, become increasingly cheap and effective at making predictions, the value and demand for skills such as human judgment and creativity will increase dramatically.^{7 8 9}

However, any of these skill sets in isolation are not enough to be considered competitive in the labour market. Today's modern workplace requires employees to be in possession of a complex suite of technical and complementary skills. For example, across the US, jobs involving a high degree of social interaction expanded by 12 percentage points between 1980 and 2012. Meanwhile, math-intensive jobs that require fewer social skills (including a number of science, technology, engineering, and mathematics (STEM) occupations) contracted by 3.3 percentage points. Jobs requiring a high degree of both math and social skills experienced particularly strong employment and wage growth.¹⁰ In another study, it was shown that cognitive and social skill requirements in job advertisements predict occupational wage differences across labour markets, even when controlling for education and experience requirements.¹¹

Research examining the dynamics of evolving skills demand has tended to be more directional, and often lacks granular insights into what specific digital skills employers are looking for and how they coincide with other non-digital skills. This report seeks to fill some of these gaps in the Canadian context, to produce a more granular picture of the specific digital skills Canadian employers are seeking.

M E T H O D O L O G Y

DATA OVERVIEW

This study relied on data from Burning Glass, an analytics software company that analyzes data from hundreds of millions of online job postings across the globe to provide real-time information on the jobs and skills that employers are looking for. This data can help to close many of the gaps left by traditional sources of labour market information (LMI), in particular when it comes to timely data on skills demands across the economy.

For this report, we used six years of online job postings covering nearly all English-language

online job postings in Canada. The first job posting considered for this report was posted on January 5th, 2012, and the last job posting considered for this report was posted on December 31st, 2018.

In total, there were more than 7 million job postings, 6.6 million of which were directly connected to an existing occupational group. These 6.6 million job postings were used as the main unit of analysis in the report.



Anatomy of a job posting

Throughout this report, we relied on job postings data gathered from Burning Glass as the basis of our research. This is a unique dataset that has several important features. Most importantly, job postings characterize a flow (potential new workers), as opposed to the stock of current workers. As a result, the number of job postings may or may not reflect the number of people working in such roles.

Secondly, a job posting is not a perfect characterization of the skills involved in performing a specific role. It is a reflection of what the hiring

party (such as employers, human resource departments, and recruiters) believes the role entails.

Therefore, it must be stressed that any insights coming from job postings data reflect employer beliefs about jobs and skills needed for their organization at the time when the posting is made — or their wish list. Employers may not expect that the successful candidate will possess all of the listed skills. Additionally, the content of job postings varies; some may be very detailed, while others offer comparatively limited information.

The Opportunity:

The Brookfield Institute for Innovation and Entrepreneurship is seeking an **Economist** to produce quantitative and qualitative research, analysis and written products to help support building a robust, data driven and user experience driven picture of Canada's innovation and entrepreneurship policy landscape and of how Canadians from different communities interacts with this landscape. The Economist will work with the Director and the broader team to develop actionable policy recommendations and to inform the design of pilots, programs and other initiatives related to innovation and entrepreneurship.

Qualifications:

Successful completion of a post-secondary **degree program in Economics** or relevant field of study required.

A minimum of **2 years of relevant professional work experience**, including: Making a major contribution to designing and conducting quantitative research, analysis and writing in a full-time role.

Directly or indirectly supporting the communication of research results to external audiences

Working in a fast-paced environment with multiple and overlapping deadlines
Experience working with large datasets

Using statistical software, such as **Stata, SPSS, Python, R, or other equivalents**

Experience working with large data sets and using statistical software such as Stata, SPSS, Python, or other equivalents

Proven ability to gather, synthesize and analyze complex information from a variety of sources, to identify trends in data and research, and to develop specific recommendations; strong logical reasoning and intellectual curiosity

Ability to apply sophisticated statistical, mathematical and computational methods to clean and analyze quantitative data

Excellent **time management, organizational and problem-solving skills**

Strong understanding of the policy process, and of government players, processes and programs

Ability to work professionally with a wide range of stakeholders, including government officials, business leaders, academics, entrepreneurs and others

Ability to clearly communicate complex issues, and **make research accessible** to maximize the impact of the Institute's work

Knowledge of key issues relating to innovation and entrepreneurship in Canada and an understanding of the Institute's mission

Knowledge of and ability to apply the principles of macro and microeconomics
Advanced statistical and econometrics knowledge

Knowledge of available Canadian economic data including

Computer proficiency, including the use of the **Microsoft Office Suite**.

The Job Posting states the company, as well as the position being hired.

It also lists educational credentials, and previous experience.

Specialized digital tools/software are listed.

Specific non-digital skills are enumerated.

Some skills may be implied but not explicitly listed (e.g. Data Visualization)

Specialized knowledge may also be required.

Representativeness of the data

Job postings were collected for all 13 provinces and territories in Canada; however, only data from English-language postings was collected, due to the platform — at this stage — being optimized only for processing job postings in English. This

is reflected in the distribution of job postings. For Quebec, the inability to parse job data in French meant that the share of job postings data was much lower than the province’s overall share of employment.

Table 1: Distribution of Job Postings Captured by Burning Glass across Canada

Province/Territory	Number of Job Postings (cumulative 2012-2018)	Share of Burning Glass Job Postings	Share of Employment ¹²
British Columbia	1,071,217	14.9%	13.5%
Ontario	2,946,740	41%	39.0%
Manitoba	193,378	2.7%	3.4%
Alberta	1,103,817	15.3%	12.3%
Nova Scotia	203,508	2.8%	2.4%
Quebec	1,044,653	14.5%	22.8%
Saskatchewan	363,185	5%	3%
New Brunswick	129,694	1.8%	1.9%
Newfoundland and Labrador	85,515	1.2%	1.2%
Northwest Territories	9,117	0.1%	<0.1%
Yukon Territories	7,510	0.1%	<0.1%
Prince Edward Islands	28,395	0.4%	0.4%
Nunavut	6,254	0.1%	<0.1%

To test the representativeness of this dataset, we examined how Burning Glass job postings data corresponds to Statistics Canada’s Job Vacancy and Wages Survey (JVWS). The JVWS captures job openings regardless of whether they are posted online or offline. However, some sample variation is inevitable as the JVWS has a smaller (random) sample size compared to Burning Glass. The JVWS also does not capture the kinds of skills employers are looking for.

JVWS was first conducted in 2015 and is conducted quarterly, every January, April, July, and October. As such, we also compiled job postings data captured by Burning Glass in those four months, for four years: 2015, 2016, 2017, and 2018. Specifically, we looked at the share of job postings in both Burning Glass and JVWS that came from one of Canada’s major occupational groups.¹³

Overall, the job postings data in Burning Glass corresponds well with the JWWS. However, there are some discrepancies. For example, Burning Glass has considerably fewer job postings, in terms of proportion, from sales and service occupations, while having a higher share of jobs from manufacturing, natural and applied sciences, and management occupations. The correlation between the two series is 0.8775.

We also compared the share of job postings in an occupation to the number of people working in that occupation according to the 2016 Census. Burning Glass data has a lower share of postings in sales and service occupations, and a higher share of postings in natural and applied sciences and related occupations. Apart from these discrepancies, the two sources are remarkably similar.

We also examined whether job postings disproportionately represent more- or less-skilled workers in Canada. As a proxy, we compared the education credentials asked for by employers in job postings to the educational attainment of individuals working in those same occupations using the 2016 census. As a blunt instrument, we calculated the share of workers and job postings with a bachelor's degree or above.

Looking at the distribution of degrees, most occupational groups are similar between the two data sources. However, three occupational groups stand out, all of which have a higher share of postings in Burning Glass asking for bachelor's degree or above. These are management occupations, natural and applied sciences and related occupations, and business, finance, and administration occupations.

From these series of representativeness checks, we can conclude that, overall, Burning Glass is a fairly representative snapshot of the Canadian labour market, despite missing French language job postings. There are some areas of overrepresentation, in particular when it comes to sales and service and natural and applied science occupations, and those that require degree credentials. The technical appendix gives further

details surrounding representativeness checks on the data.

DEFINING DIGITAL SKILLS

To understand the universe of skills that Canadian employers are looking for, we first sought to refine our understanding of what makes a skill digital. It's clear that when an employer asks for proficiency in a specific software, they are asking for a digital skill. However, other skills, which are decidedly digital, such as machine learning, might not list specific programming languages, but knowledge in at least one is implied. Other cases are even more complex — for example, should 'social media', a skill in our sample that is highly associated with the use of digital tools, but isn't a digital tool itself, be considered digital?

To address this challenge, we began by examining skills that were clearly digital in the data, using existing taxonomies in Burning Glass data. We then augmented this analysis by identifying the skills that consistently show up in digitally-intensive occupations,¹⁴ labelling those above a certain threshold as digital. We devised several robustness checks to minimize the risk of non-digital skills being classified as digital skills. Consistent with previous studies, this enabled us to examine digital skills along a spectrum based on their digital intensity.¹⁵

Digital skills as a spectrum

First, we leveraged existing skills taxonomies devised by Burning Glass to define a set of core digital skills, which included software, as well as skills in the following pre-assigned clusters: Information Technology, Analysis, E-Commerce, Web Analytics, and Bioinformatics.¹⁶ The clusters were chosen through manual examination of the skills that were clearly digital.

Second, to construct a digital intensity measure for every skill, we leveraged the existing measure of digital skill intensity across 4-digit National Occupation Classifications (NOCs), used to define tech occupations in Vu, Zafar, and Lamb (2019). This

digital intensity measure ranks occupations based on six job attributes that relate to technology use or production from the US O*NET database. If a skill frequently appears only in highly-digital jobs, it will have a high digital intensity score, and vice versa. The technical appendix details the full procedure and modifications we made for this report. We also confirmed the robustness of this approach using available measures.

Once we identified the digital intensity for each of the 13,000 skills in the database, we defined a cutoff that would create two distinct categories: digital skills and non-digital skills. To do so, we built a logistic regression that estimated the probability of a skill, with a particular digital intensity, appearing within one of Burning Glass's previously defined core digital skills clusters and our additions. If a skill had a 50 percent or more probability of appearing within one of these defined digital skills clusters, it was classified as a digital skill. We also tested our analysis with a lower cut-off; none of the results of this report were affected by that change.

Skills clustering

Using our definition, we examined what combinations of digital skills employers are looking for and how they overlap. Here, we examined only connections between digital skills; non-digital skills were not yet considered. A common approach in analyzing networks involves understanding the network's community structure.¹⁷ A community is a group of skills that have many connections to one another in the same community, and not many connections to skills in other communities.

The communities in a network allow us to understand important divisions between elements in that network — in our case, each skill represents an element. In practice, there are many different conceptual frameworks and specific algorithms that can be used to define communities.¹⁸ However, we restricted our choice based on the data and our research focus. Specifically, in the network of skills available through Burning Glass, the strength by which two skills are connected depends on how frequently these skills show up

in each job advertisement together. As a result, connections between general skills such as 'communications' showed up many more times than between two specialized, but related, skills, such as 'Python' and 'machine learning'. Ideally, our choice of community detection algorithm should deemphasize the importance of these often-mentioned general skills, and avoid letting them define the communities.

Additionally, as our network was fairly large, algorithms with a straightforward computational complexity were also prioritized.¹⁹ This led us to select a class of algorithms known as modularity, which measure how likely it is that a given community structure is observed if all the skills in the network are connected at random. However, modularity-based measures have a number of limitations, such as a resolution problem,²⁰ which describes their inability to recognize communities smaller than a specified size.

We have addressed this issue in two ways.²¹ First, we performed the community detection algorithm separately for the group of digital and non-digital skills identified. As the resolution problem depends on the size of the input network, this division reduced the size of the individual network being clustered, allowing us to examine smaller communities. Second, we used two different modularity-based algorithms that employ different strategies to find the communities. Using two algorithms enables a more granular understanding of different skill clusters and how they relate to each other. Further information can be found in the technical appendix.

THE ANATOMY OF DIGITAL SKILLS DEMANDS IN CANADA

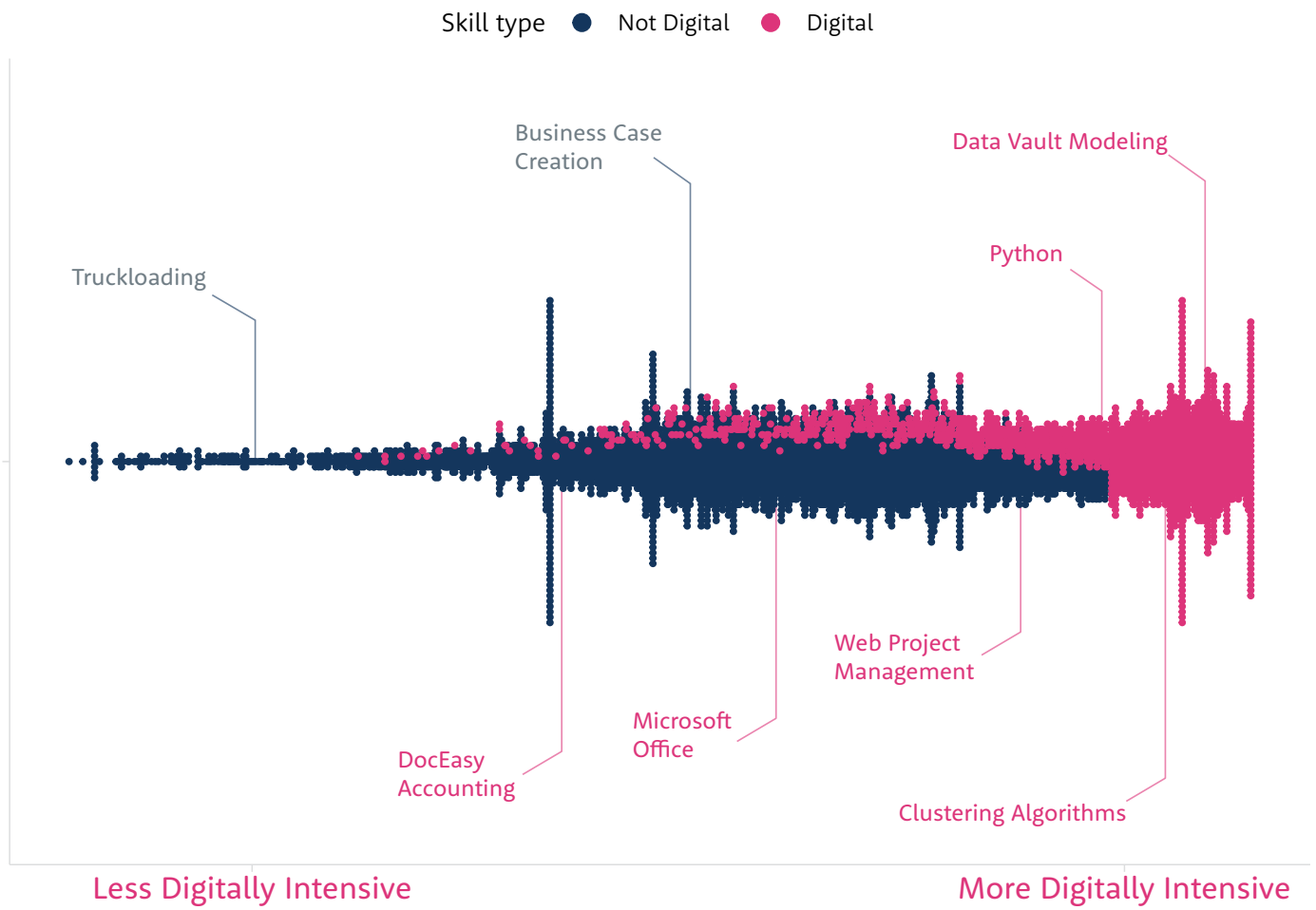
SUMMARY

In this section, we outline our approach to defining digital skills based on a skill's digital intensity. Using this novel approach, we were able to define 3,600 unique digital skills. Each of these skills exists on a spectrum depending on their overall digital intensity. This spectrum ranges from less digitally-intensive skills, such as general spreadsheet skills, to much more digitally-intensive skills, such as those involved in machine learning.

We also examined the digital skills Canadian employers ask for the most. Unsurprisingly, the most in-demand digital skills are less digitally-

intensive, in particular those associated with the Microsoft Office Suite software. However, many employers are also looking for much more digitally-intensive skills related to data analysis, including SQL and SAP, indicating the importance of data and data analysis skills in today's economy. Canada's growing digital economy is also reflected in the large number of times employers asked for general software skills, as well as specific programming languages such as Java.

Figure 1
 Identified Digital Skills



Source: Author Calculations
 Note: Each dot is a skill

THE DIGITAL SKILLS SPECTRUM

Previous Brookfield Institute studies articulate digital literacy as a spectrum of skills, ranging from the baseline digital skills that all Canadians need to participate in an increasingly digital economy, to much more specialized digital skills involved in the creation of new digital products and services.²² We build off this framework, defining skills along a spectrum based on their digital intensity, up to a threshold that best captures the skills that are decidedly digital. Out of the 13,000 unique skills that show up in Canadian job advertisements, 3,600 met our digital threshold.

Figure 1 illustrates the spectrum of digital skills. At the far left of the spectrum are the skills that show up frequently in job postings attached to the most digitally-intensive occupations. These include highly technical digital skills and knowledge, such as those associated with: data vault modeling, for long-term storage of data; clustering algorithms, a machine learning technique designed to group data points; and programming languages, such as Python. The digital skills attached to less digitally-intensive occupations are associated with, for example, web-based project management, Microsoft Office, and accounting software.

THE DIGITAL SKILLS EMPLOYERS ASK FOR THE MOST

In addition to examining the digital intensity of skills, we also highlight the digital skills that are most in-demand from Canadian employers. Unsurprisingly, by sheer volume of mention, employers are looking for software skills associated with general office tasks, in particular use of the Microsoft Office Suite. These skills have a low digital intensity. However, other more digitally-intensive general office skills are also in high demand, including SAP, an enterprise resourcing software.

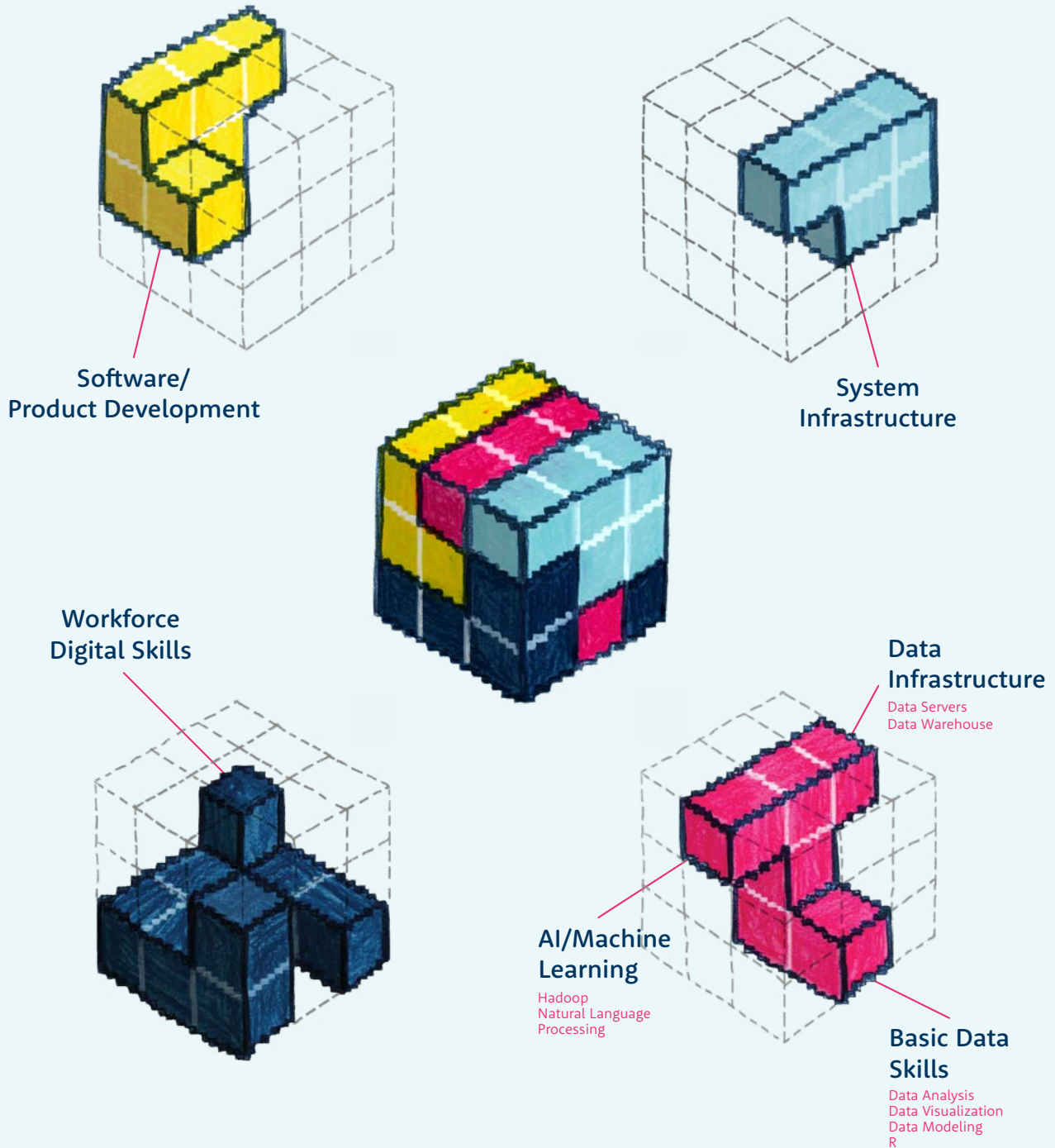
Interestingly, Microsoft Excel was mentioned almost three times more than Microsoft Word. This is likely driven by employers' assumptions about a worker's baseline level of knowledge in specific roles, but also reflects the importance of data skills across sectors — a conclusion that is reinforced by the high frequency at which general spreadsheet skills and the more digitally-intensive data software, SQL, was mentioned.

The importance of more digitally-intensive skills across Canada's economy is also reflected in the number of times employers asked for general software skills, as well as knowledge of specific programming languages such as Java.²³

Table 2: Top 10 Digital Skills by Number of Job Postings That Mention Them

Skill	Description	Number of mentions	Digital intensity classification
<i>Microsoft Excel</i>	Spreadsheet software	741,191	Low
<i>Microsoft Office</i>	Work productivity software suite	621,690	Low
<i>Microsoft Word</i>	Document composing software	296,992	Low
<i>Microsoft PowerPoint</i>	Presentation creation software	266,748	Low
<i>SQL</i>	Database management software	163,000	High
<i>Spreadsheets</i>	Data organization	151,719	Low
<i>Software Development</i>	General skill	133,681	High
<i>Technical Support</i>	General skill	130,540	Medium
<i>SAP</i>	Business enterprise software	126,787	Medium
<i>Java</i>	Programming language	112,680	High

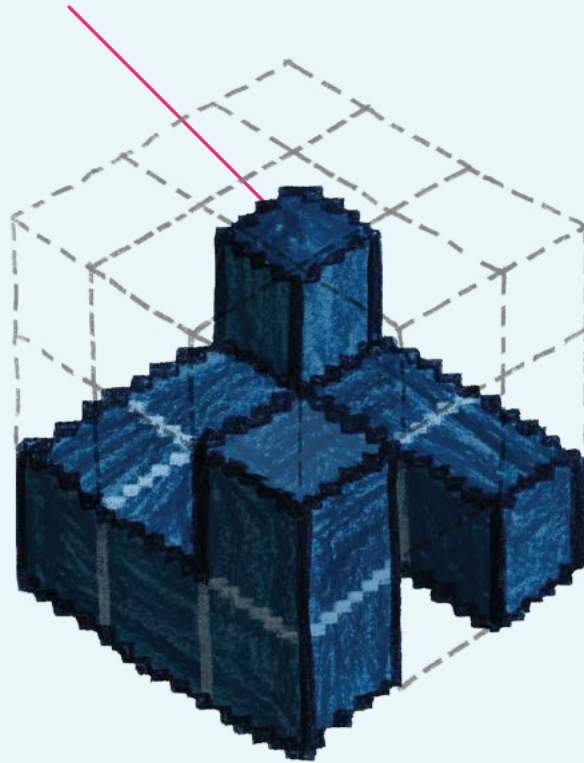
DIGITAL SKILLS FRAMEWORK



Within the broad category of digital skills exist four unique clusters that show up in job postings together: general workforce digital skills, data skills, system infrastructure skills, and, finally, software and product development

skills. While these skills form unique clusters, data skills in particular are so frequently requested in different occupations with varying digital intensity that they also act as a connector between the three other digital skill clusters.

Workforce Digital Skills



WORKFORCE DIGITAL SKILLS

This skill cluster is the most general and least digitally-intensive, consisting of 997 unique skills used by workers across many industries. The skills range from those associated with general office tasks to those associated with specific professions, such as use of architectural and engineering-based software to augment existing job tasks and business processes.

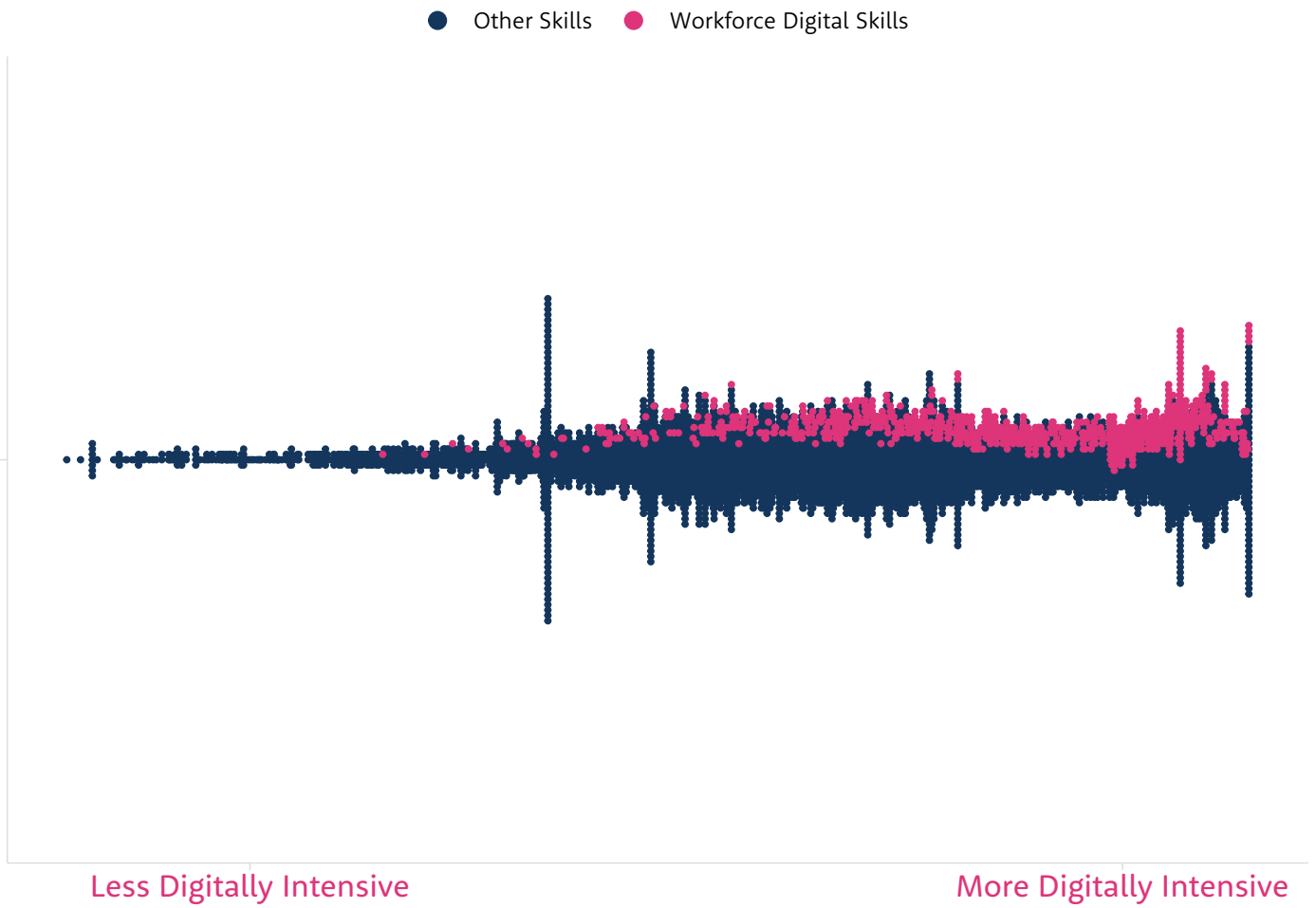
Some prominent skills in this cluster include Microsoft Excel, Word, PowerPoint, and Office (741,191, 296,992, 266,792, and 621,690 mentions

respectively). This cluster also includes skills associated with some general-use design software, such as Adobe Photoshop (53,855 mentions), as well as general data analysis skills (mentioned 60,256 times) and use of tools such as SAS (21,130 mentions).

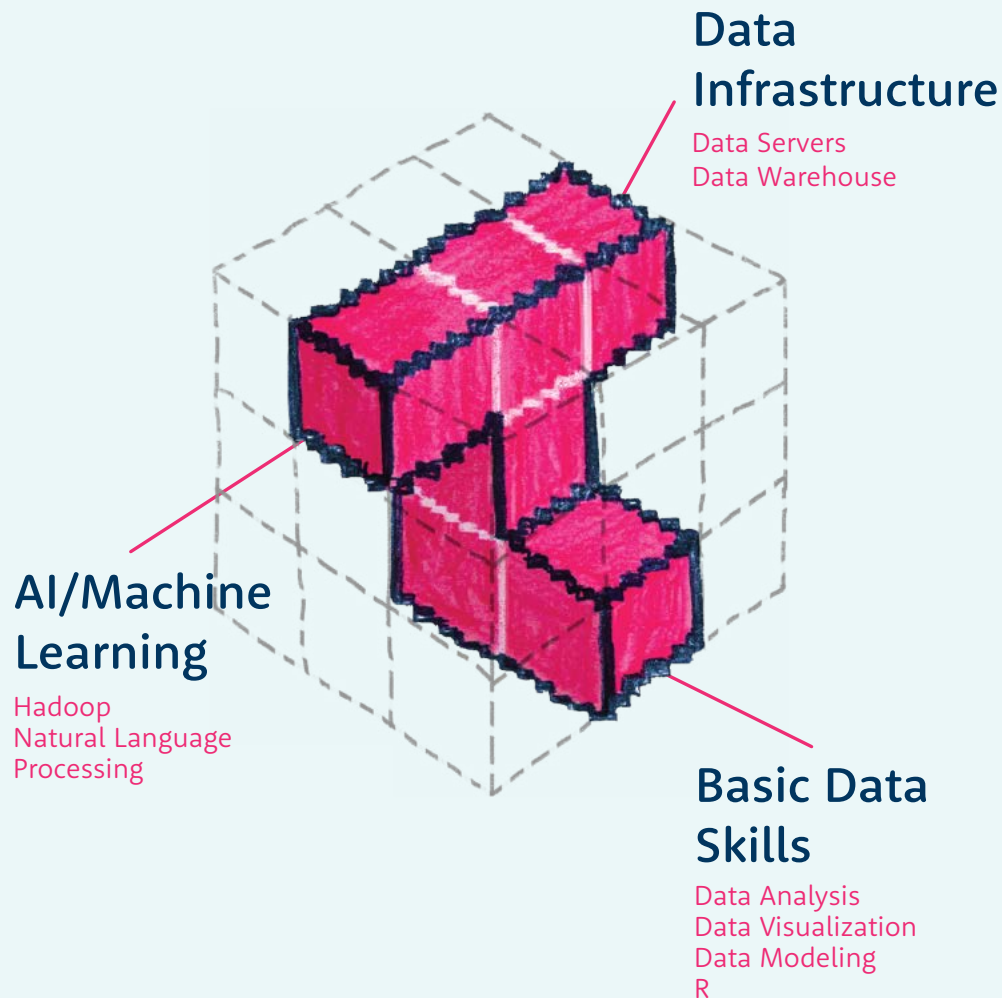
Based on the average weight of our previously defined digital intensity scores, skills in this cluster are the least digitally-intensive, and most in-demand across the economy.

Figure 2

Workforce Digital Skills



Source: Author Calculations
Note: Each dot is a skill



DATA SKILLS

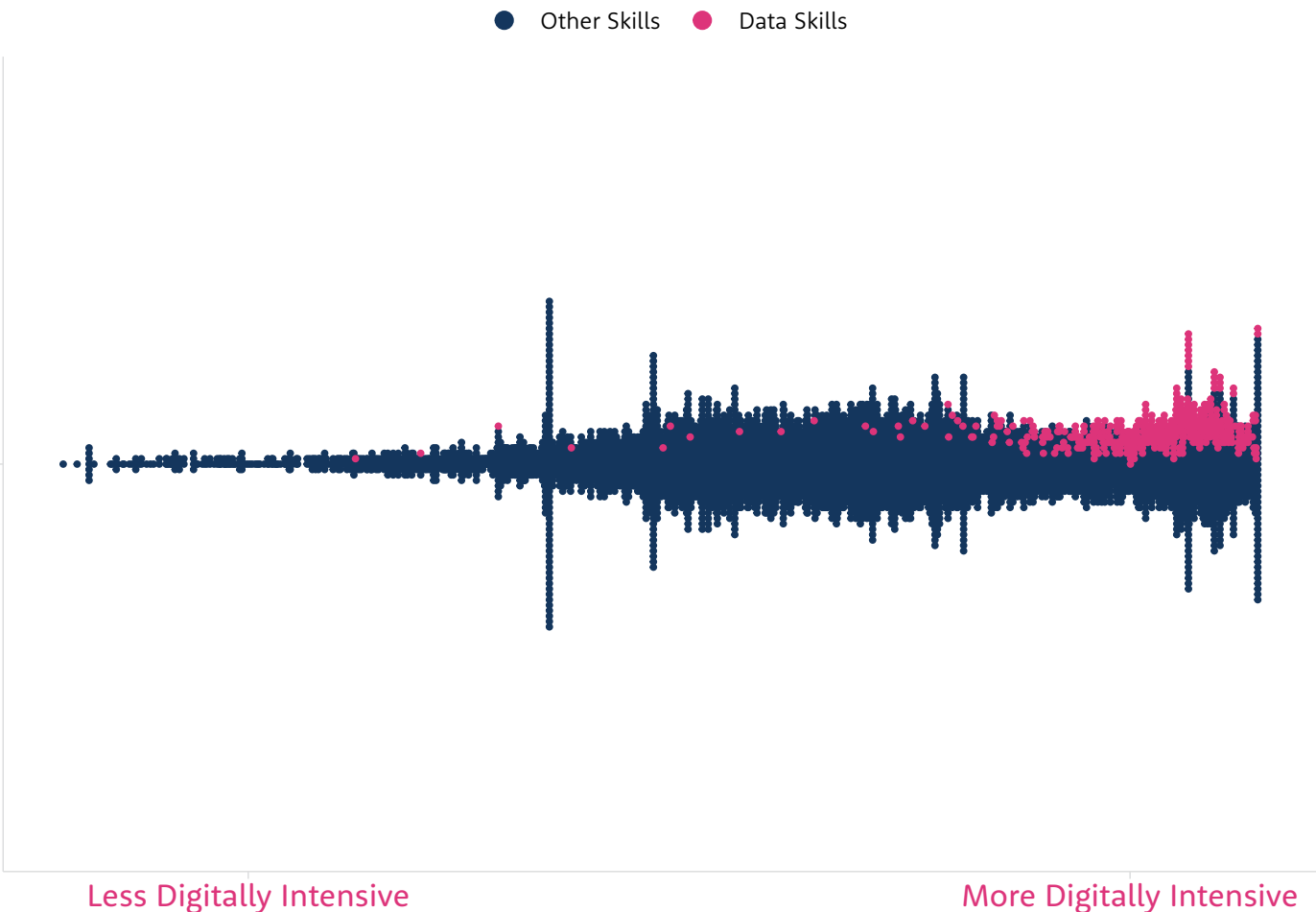
This skill cluster consists of 507 unique skills focussed primarily on data gathering and analysis, especially in large-scale enterprise analytics. Some prominent skills in this cluster include “Data Modeling” (20,252 mentions), “Big Data” (13,173 mentions), and “Business Intelligence” (35,361 mentions), as well as skills associated with specific data analytics tools, such as Apache Hadoop (10,509 mentions), Tableau (9,121 mentions), and R (4,132 mentions).

Data skills have a unique sub-cluster structure, illustrated above. There is a strong separation

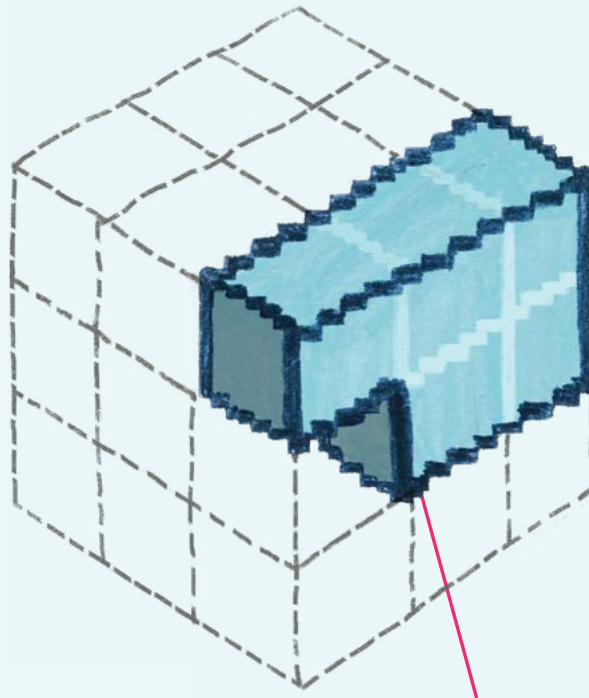
of basic data skills, which straddle the Data and Workforce Digital Skills clusters, and advanced data skills, where two further sub-clusters of skills exist: Data Infrastructure, which exists alongside the System Infrastructure cluster, and AI/Machine Learning skills, which appears alongside the Software/Product Development cluster.

Data skills are important across the economy and have a wide variance in their digital intensity. As a result, the overall digital intensity of this cluster exceeds only the Workforce Digital skills cluster.

Figure 3
Data Skills



Source: Author Calculations
Note: Each dot is a skill



System Infrastructure

SYSTEM INFRASTRUCTURE SKILLS

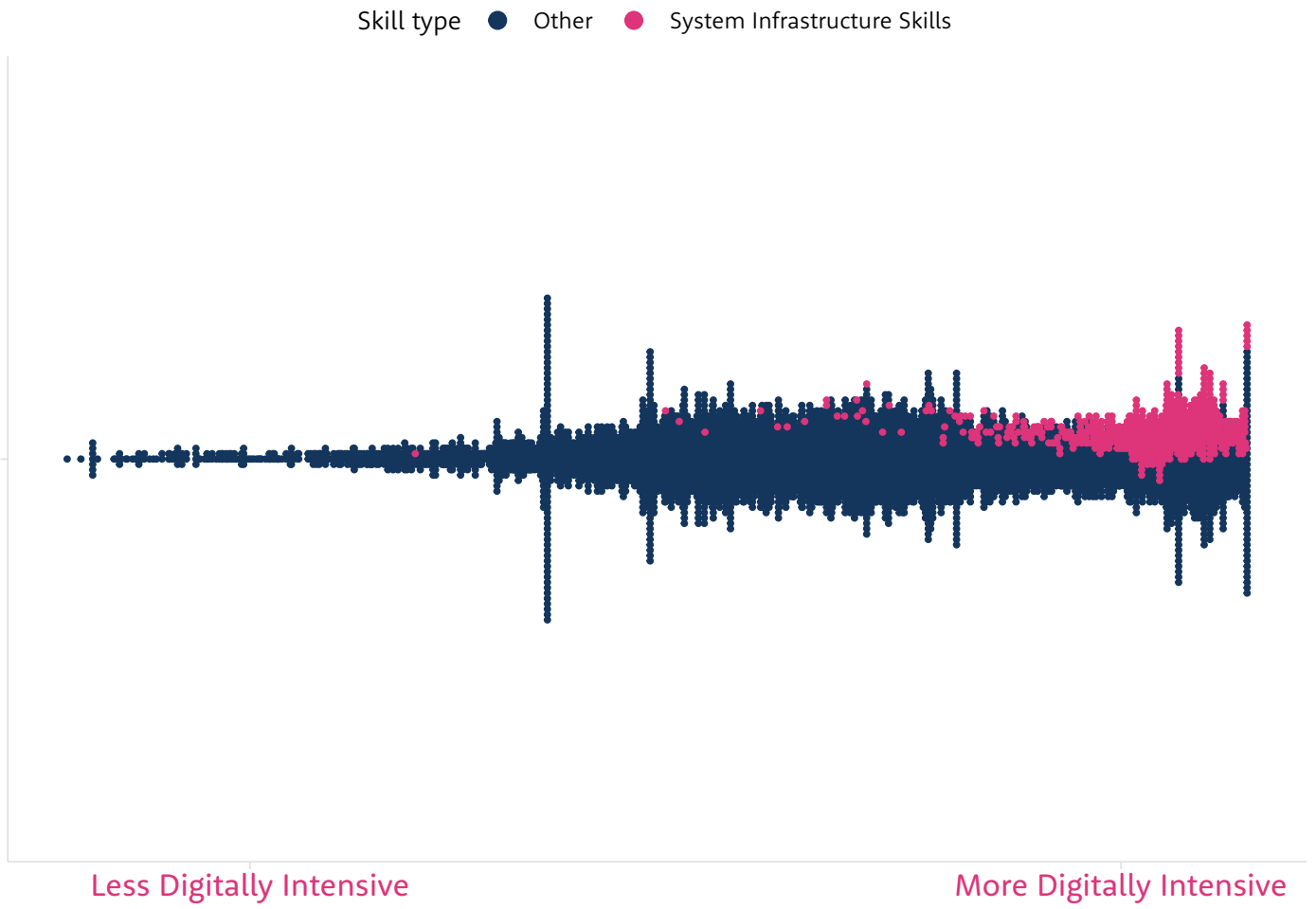
This skill cluster consists of 985 unique skills that pertain to digital infrastructure management, ranging from setting up and managing cloud computing services to more general IT support. Some prominent skills in this group include proficiency with specific platforms such as VMWare (25,319 mentions) or Windows Server (21,094 mentions), and general support skills such as

‘system administration’ (33,459) and ‘hardware and software installation’ (23,940 mentions).

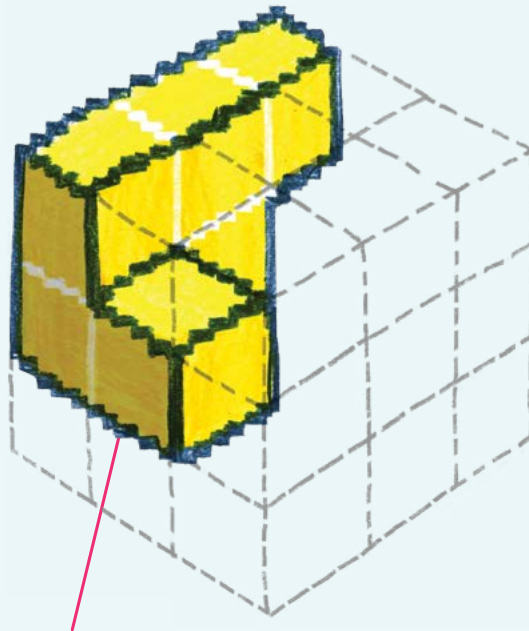
This cluster is the second most digitally-intensive. The overall digital intensity of this cluster is lower than that of the Software/Product Development Skills cluster because of the general IT support skills that are included.

Figure 4

System Infrastructure Skills



Source: Author Calculations
Note: Each dot is a skill



Software/ Product Development

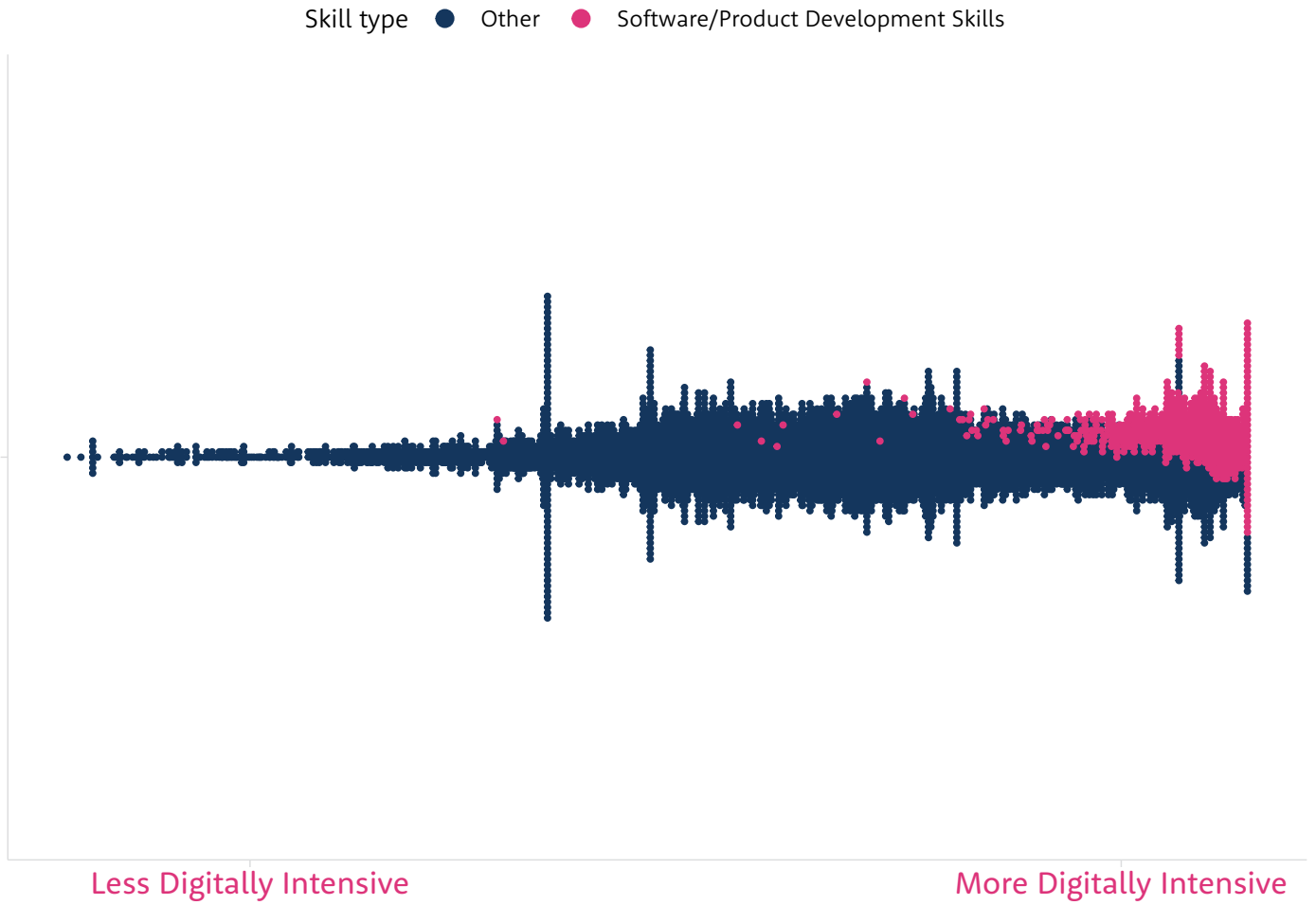
SOFTWARE / PRODUCT DEVELOPMENT SKILLS

This skill cluster consists of 1,109 skills that pertain to the generation of new digital products, both web- and software-based. Some prominent skills in this group include proficiency in specific programming languages, such as Java (112,680) and Python (43,137 mentions), and general skills such as ‘software development’ (133,681 mentions),

‘software engineering’ (47,775 mentions), and ‘web development’ (41,184 mentions). Some technical design skills, pertaining specifically to web development, are also a part of this cluster. On average, skills in this cluster are the most digitally-intensive.

Figure 5

Software/Product Development Skills



Source: Author Calculations
Note: Each dot is a skill

HYBRID JOB TRENDS : COMBINING DIGITAL AND NON-DIGITAL SKILLS

OVERVIEW

Employers rarely ask for digital skills in isolation. Rather, consistent with interest in STEAM (science, technology, engineering, arts, and mathematics) education, and with recent studies pointing to demand for digital and soft skills, they are often looking for people with combinations of skill sets from digital and non-digital domains. We have uncovered four prominent trends related to the demand for

these hybrid jobs in Canada. These insights could help students, workers, and job seekers make more informed decisions about how to augment existing skills to make themselves more valuable to potential employers or more resilient to future changes in skill demand. They could also help to inform policymakers, educators, and workforce developers looking to design new programs or interventions, or augment existing ones.

Summary of hybrid job trends:

- The basket of skills needed, across a large number of jobs and industries, includes a combination of baseline workforce digital skills, in particular related to use of the Microsoft Office Suite of tools, as well as a broad suite of non-digital skills, such as interpersonal, problem-solving, and project management skills. This suggests that most Canadians would benefit from developing these skills, in terms of their ability to gain employment, compete, and adapt in Canada's labour market.
- Software development, systems infrastructure, and highly technical data roles are the most digitally-intensive, and also the most hybrid, meaning that in addition to digital skills, employers ask for non-digital skills at a higher intensity compared to other roles. To reflect the creative and collaborative nature of the work, employers are looking for candidates who are proficient in a variety of digitally-intensive tools, but not at the expense of strong interpersonal, project management, and problem-solving skills.
- There are a large number of creative jobs that blur the lines between the arts, communications and media, design, and digital skills. In these roles, the core creative practice remains the most important element of the job, but in most instances must be augmented with design-oriented digital tools.
- Data skills are critical in today's economy, from less digitally-intensive roles, such as office support occupations, to more digitally-intensive occupations in software development. For individuals looking to break into some of these more digitally-intensive roles, upgrading data skills may be a good starting point, although additional credentials and upgrades may be required.

CANADIANS, ACROSS JOBS AND INDUSTRIES, COULD BENEFIT FROM A BASKET OF SKILLS THAT INCLUDES BASELINE DIGITAL SKILLS AND COMPLEMENTARY SOFT SKILLS

“It really depends on the group that you’re in, but everyone needs to feel comfortable using a computer and the software they need to use on the job. If you can’t use a laptop, Microsoft Office Suite, programs like Excel or PowerPoint, it’s game over. Especially Excel—it’s one of the best basic skills you could have.”

—Andrea Niles-Day, Director of Project Governance and Performance Measurement, RBC Capital Markets

(Quote taken from Huynh & Malli, 2018)

As the use of digital tools has become indispensable across the economy, Canadian employers need candidates with general workforce digital skills to conduct daily tasks. Regardless of the level of skill a worker might hold, proficiency in using baseline digital tools is essential. Alongside these digital skills, employers are also looking for candidates with a broad suite of soft skills essential in most work contexts. These primarily relate to communications and organizational skills, interpersonal interactions, problem-solving, and project management skills.

Workforce digital skills are pervasive, regardless of the credentials required for a job

General workforce digital skills are some of the most likely to appear in a job posting, and are present in roughly one third of Canadian job postings from our sample data.²⁴ These skills are in-demand, regardless of the level of education required for a job, and are largely complements to other skill sets. There are no occupations where the majority of skills listed are workforce digital skills; however, between 5 to 20 percent of occupations have a moderate level of workforce digital skills listed.

Workforce digital skills cover many occupational and industrial contexts, and generally fall into one of two categories. The first relates to the tools and software that are generally applicable across the workforce. This includes the ability to use the software included in the Microsoft Office Suite, which appears in the most job postings compared to other digital skills.²⁵ Second are the skills and software that have more specialized business functions. This includes software such as SAP for inventory management, Peoplesoft for talent management, as well as some highly specialized digital tools, such as SolidWorks, for engineering simulations.

When we examine workforce digital skills in occupations that require a university degree versus those that do not, the demand for these skills remains relatively constant. In fact, more than half of the 66,000 job postings asking for ‘word processing’, and more than 43 percent of the 82,000 job postings asking for ‘spreadsheet skills’, only require a high school diploma as a minimum degree requirement.

When employers ask for workforce digital skills, they also want a candidate with a broad suite of soft skills

In addition to much more occupation-specific skills, when an employer asks for workforce digital skills, they also request that the candidate be in possession of a broad suite of soft skills. The two skills that are most likely to show up are ‘communications’ and ‘organizational skills’, which appear in over 50 percent and 25 percent, respectively, of job postings that require at least one workforce digital skill.

Other soft skills likely to appear alongside workforce digital skills include interpersonal skills, such as ‘teamwork’, ‘collaboration’, and ‘customer service’. Project management skills, such as ‘budgeting’ and ‘planning’, are also frequently requested, as well as more general skills and aptitudes such as ‘problem-solving’ and ‘detail-orientedness’. Finally, employers are also looking for candidates with strong writing skills.

Occupation examples

Executive Assistant

Coordinate administrative procedures, public relations activities and research and analysis functions for members of legislative assemblies, ministers, deputy ministers, corporals and executives, committees and boards of directors. They are employed by governments, corporations and associations.

- + In 2016, there were **47,975** Executive Assistants in Canada.
- + Between 2012 and 2018, there were **23,366** job postings for this occupation.

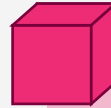
48.5% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Administrative Support
- File Management
- Organizational Skills
- Financial Record Compilation
- Oral Communication
- Secretarial Skills

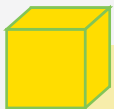
18.8% Workforce Digital Skills



Skills in a typical job posting

- Microsoft Excel
- Microsoft Word

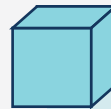
19.5% Communications Skills



Skills in a typical job posting

- Written Communication
- Copy Editing

11.7% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Tax Preparation

Occupation examples

Civil Engineer

Perform engineering duties in planning, designing, and overseeing construction and maintenance of building structures, and facilities, such as roads, railroads, airports, bridges, harbors, channels, dams, irrigation projects, pipelines, power plants, and water and sewage systems.

- + In 2016, there were **53,900** Civil Engineers in Canada.
- + Between 2012 and 2018, there were **27,676** job postings for this occupation.

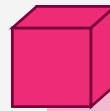
38.6% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Administrative Support
- File Management
- Organizational Skills
- Financial Record Compilation
- Oral Communication
- Secretarial Skills

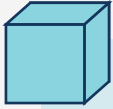
20.9% Workforce Digital Skills



Skills in a typical job posting

- AutoCAD
- Microsoft Office
- Primavera

24.1% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Writing
- Communication Skills
- Problem Solving

12.3% Communications Skills



Skills in a typical job posting

- Building Effective Relationships

**IN HIGHLY TECHNICAL ROLES,
STRONG DIGITAL SKILLS ARE
NECESSARY — BUT NOT AT THE
EXPENSE OF STRONG SOFT SKILLS**

“[When I hire,] I look for good communication and critical thinking skills—for the ability to ask good questions. Developers need to be able to listen to people state a problem and convert that into a system that combines computers doing kind of ugly, clunky things in a way that hopefully makes sense. Most of that is about listening properly and translating.”

—Florescia Herra-Vega, CTO, Peerio

(Quote taken from Huynh & Malli, 2018)

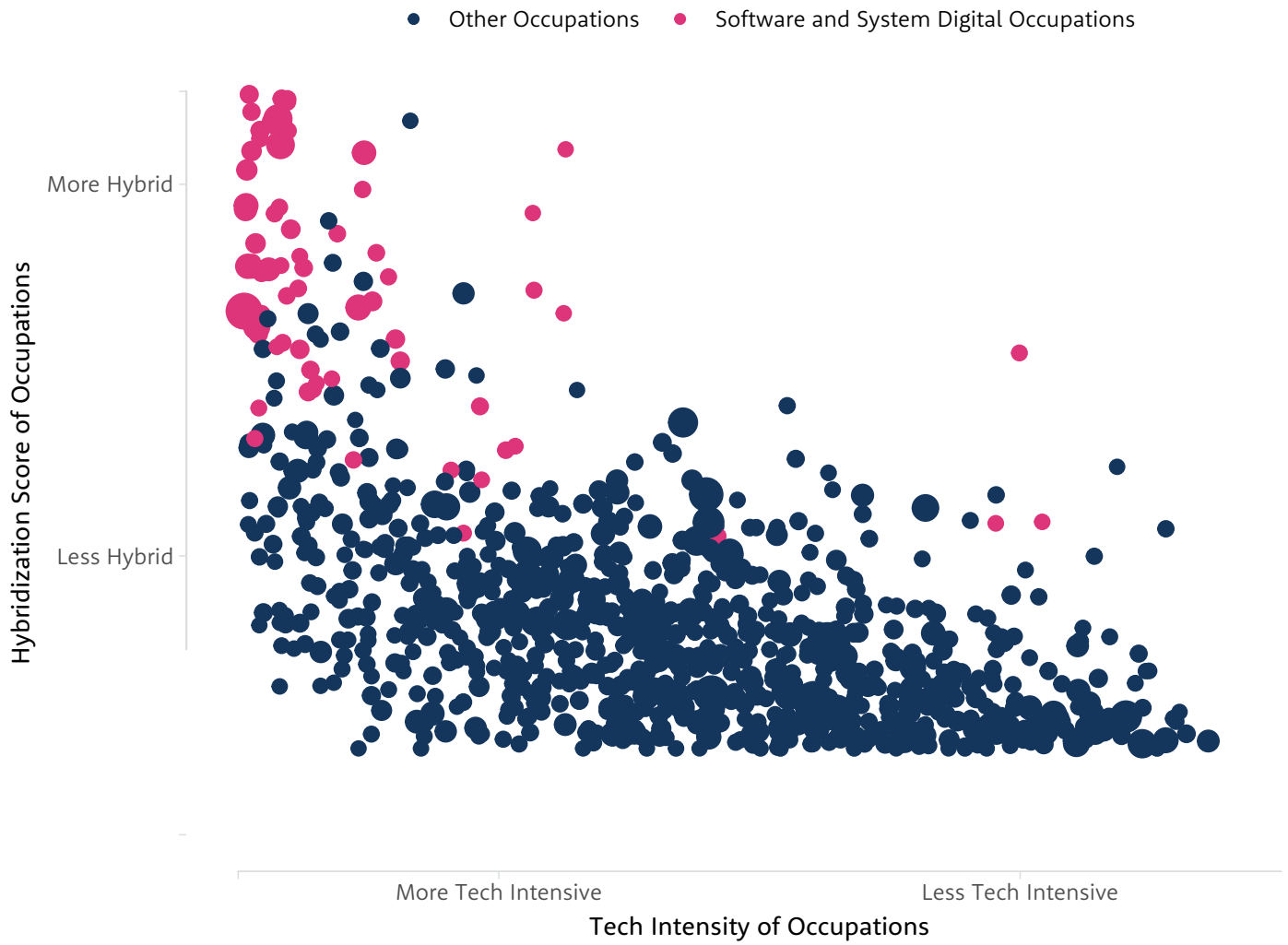
The most highly digital occupations — those that have a high proportion of skills coming from the Software/Product Development and System Infrastructure clusters, as well as advanced data skills from the Data Skills cluster — are also the most hybrid. In addition to digital skills, employers list non-digital skills from different domains at an intensity that exceeds that of all other roles.

Firms hiring for these highly digital roles are looking for employees with a particularly interdisciplinary skill set, reflecting the highly

creative and collaborative nature of many of these jobs. Digital skills are therefore necessary, but insufficient. For example, software developers operate in an exceptionally team-driven environment; in addition to their technical abilities, employers also want to make certain that they have the ability to communicate effectively and work in a team setting to develop ideas and solve problems collaboratively.²⁶

Within these uniquely hybrid jobs, at least 10 percent of listed skills come from either the Software/Product Development or System Infrastructure Skills clusters. The non-digital skills listed most frequently for these jobs include the general soft skills that appear in job postings throughout the economy (see previous trend), as well as ‘planning’ (112,050 mentions), ‘troubleshooting’ (110,059 mentions), ‘project management’ (98,797 mentions), ‘research’ (75,516 mentions), and ‘quality assurance and control’ (64,761 mentions). This highlights the importance of project management, issue identification, judgment and problem solving, as well as maintaining high quality standards within these roles.

Figure 6
Hybridization of Digital Jobs



Source: Author Calculations

Occupation examples

Computer Systems Engineer

Design and develop solutions to complex applications problems, system administration issues, or network concerns. Perform systems management and integration functions.

- + In 2016, there were **24,935** Computer Systems Engineers in Canada.
- + Between 2012 and 2018, there were **28,697** job postings for this occupation.

26.0% Software/Product Development Skills



Skills in a typical job posting

- Software Development
- Agile Development
- Python
- SQL Server

13.3% Communications Skills



Skills in a typical job posting

- Teamwork / Collaboration
- Customer Service

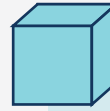
19.7% System Infrastructure Skills



Skills in a typical job posting

- Windows Server
- Secure Shell
- Virtualization

12.9% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Communication Skills
- Planning

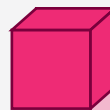
14.5% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Procurement
- Financial Management
- Project Management

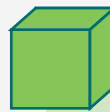
7.5% Workforce Digital Skills



Skills in a typical job posting

- Technical Support

5.6% Data Skills



Skills in a typical job posting

- Data Architecture

Occupation examples

Information Technology Project Manager

Plan, initiate, and manage information technology (IT) projects. Lead and guide the work of technical staff. Serve as liaison between business and technical aspects of projects. Plan project stages and assess business implications for each stage. Monitor progress to assure deadlines, standards, and cost targets are met.

- + In 2016, there were **66,000** Information Technology Project Managers in Canada.
- + Between 2012 and 2018, there were **36,081** job postings for this occupation.

30.4% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Project Planning and Development Skills
- Project Management
- Resource Management
- Budgeting
- Risk Management

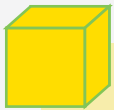
14.8% Software/Product Development Skills



Skills in a typical job posting

- Scrum Master
- Java

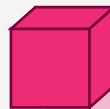
18.4% Communications Skills



Skills in a typical job posting

- Teamwork / Collaboration
- Leadership
- Workforce Planning

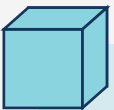
10.2% Workforce Digital Skills



Skills in a typical job posting

- Microsoft Excel
- Microsoft Sharepoint

16.7% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Writing
- Communication Skills

5.8% Data Skills



Skills in a typical job posting

- IT Management

DIGITIZATION OF COMMUNICATIONS, ART, AND DESIGN

“We’re a video game arts organization. The context we provide our programming in is art but people are learning the technical skills within it. ‘Video games’ is hard enough for people to grasp as a technical field, much less an art field. Bringing these things together helps people build the skills to express themselves creatively but also lead to a creative industry job that helps them support their art practice.”

—Jennie Robinson Faber, Executive Director, Dames Making Games

(Quote taken from Huynh & Malli, 2018)

From photography, music, and writing to advertising and video game design, many creative professions have been particularly adept at leveraging technology to improve their practices. This is exemplified in the data, where there is a high demand for workers with combinations of digital media, communications, and design skills. For many of these occupations, a candidate’s creative and design skills must be augmented by the ability to work with a variety of digital tools, from web design to the Adobe Creative Suite.

The digital, creative professional

This distinct group of skills reflects a variety of different creative occupations, from digital media and arts jobs such as graphic designers and video game producers, to advertising, communications, and marketing professionals.

The digital skills that are in-demand for these creative professionals emerge as a subcluster that straddles the Workforce Digital Skills and Software/Product Development Skills clusters. These digital skills primarily pertain to graphic design, web development, and marketing and communications. For these workers, the tools from the Adobe

Creative Suite are requested most often; proficiency in Adobe Photoshop (53,855 mentions), Adobe InDesign (34,554 mentions), and Adobe Acrobat (32,753 mentions) were the top three demanded digital skills. Commonly requested digital skills related to marketing and communications include the ability to use social media platforms — namely Facebook (30,324 mentions), LinkedIn (7821 mentions), and YouTube (6853 mentions), as well as marketing management tools such as ‘content management systems’ (13,492 mentions) and Google Analytics (10,578 mentions). Finally, employers are also looking for candidates with general web development knowledge, such as ‘website design’ (29,234 mentions) and ‘prototyping’ (12,105 mentions), which appear more often than the ability to use specific tools such as Drupal (5,706 mentions).²⁷

While these roles are quite unique from one another, they all draw on non-digital communications, marketing, and design skills. Specific in-demand non-digital skills for these roles include: creativity (63,539 mentions, appearing in 32.6 percent of jobs that mention at least one digital design skill), social media (21.5 percent), editing (17.2 percent), and graphic design (12.2 percent), in addition to the non-digital skills that are demanded across the economy.

The jobs found in this cluster are rooted in the arts and humanities, focusing on design principles, communications and marketing, and the creation of original artistic works, but are augmented by digital tools. In many cases, digital tools have become so central that it would be nearly impossible to perform these jobs without them.

Occupational examples

Graphic Designers

Design or create graphics to meet specific commercial or promotional needs, such as packaging, displays, or logos. May use a variety of mediums to achieve artistic or decorative effects.

- + In 2016, there were around **50,900** Graphic Designers in Canada.
- + Between 2012 and 2018, there were **13,648** job postings for this occupation.

38.5% Communications Skills



Skills in a typical job posting

- Graphic Design
- Branding Communication
- Creativity
- Customer Contact
- Promotional Material

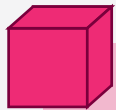
6.4% Software/Product Development Skills



Skills in a typical job posting

- Extensible Markup Language (XML)

26.5% Workforce Digital Skills



Skills in a typical job posting

- Adobe Photoshop
- Adobe Illustrator
- Digital Design

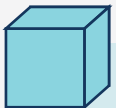
5.5% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Research

20.7% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Detail-oriented
- Critical Thinking
- Scheduling

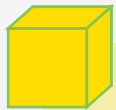
Occupational examples

Multimedia Artists and Animators

Create special effects, animation, or other visual images using film, video, computers, or other electronic tools and media for use in products or creations, such as computer games, movies, music videos, and commercials.

- + In 2016, there were **16,000** Multimedia Artists and Animators in Canada.
- + Between 2012 and 2018, there were **4,328** job postings for this occupation.

30.8% Communications Skills



Skills in a typical job posting

- Interactive Design
- Creativity
- Fine Arts

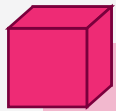
12.8% Software/Product Development Skills



Skills in a typical job posting

- Game Development

25.% Workforce Digital Skills



Skills in a typical job posting

- Maya
- Animation

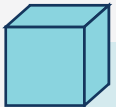
8.5% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Research

18.9% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Organizational Skills
- Planning

Data skills can act as a bridge between less and more digitally-intensive roles

“In the future, data science is not going to be an exclusive specialized area for a select few. It’s going to be part of any computerized work stream. The more computer-based and automated we become, the more data will be infused into every job and role and industry.”

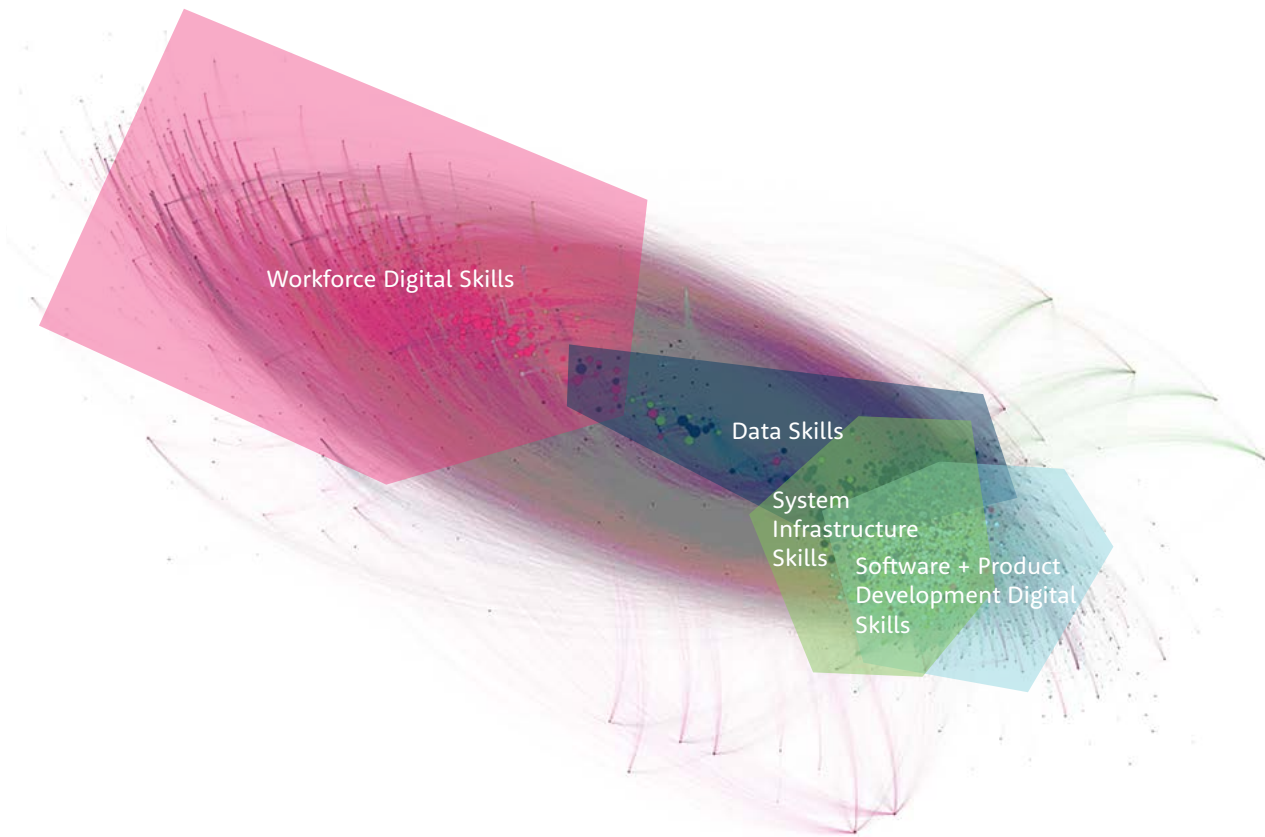
—Shingai Manjengwa, Founder and Director, Fireside Analytics Inc.

(Quote taken from Huynh & Malli, 2018)

Data skills have become essential prerequisites for roles across the economy. For most, foundational data skills such as Microsoft Excel are sufficient, but as roles become more digitally-intensive, so too do the data skills they require. Microsoft Excel, Spreadsheet, SQL, and SAP were the digital skills most listed in the collected sample of job postings between 2012-2018; all four involve the use, manipulation, and creation of data.

While there is a distinct Data Skills cluster, data skills straddle all digital skills clusters. For example, prominent baseline data skills related to Microsoft Excel and spreadsheets appear in the Workforce Digital Skills cluster, and familiarity with SQL, which is important for manipulating data, is found in the Software/Product Development Skills cluster. This suggests that data skills are important across occupations with various levels of digital intensity, and that a worker’s data skills may be applicable across many different occupations. For individuals looking to break into more digitally-intensive roles, upgrading data skills may therefore be a good starting point. We demonstrate the connecting role data skills play by showcasing the universe of skills as a network and use a force-based algorithm to visualize the distance between skills.²⁸

Figure 7
Data Skill connects Workforce Digital Skills to More Intensive Digital Skills



Source: Author Calculations

Microsoft Excel and SQL act as a bridge between less and more digitally-intensive roles

While data skills clearly straddle digital skills clusters, it is useful to know what specific data skills are requested together to understand how an individual might leverage and build on their existing skill sets to enhance their competitiveness in the labour market.

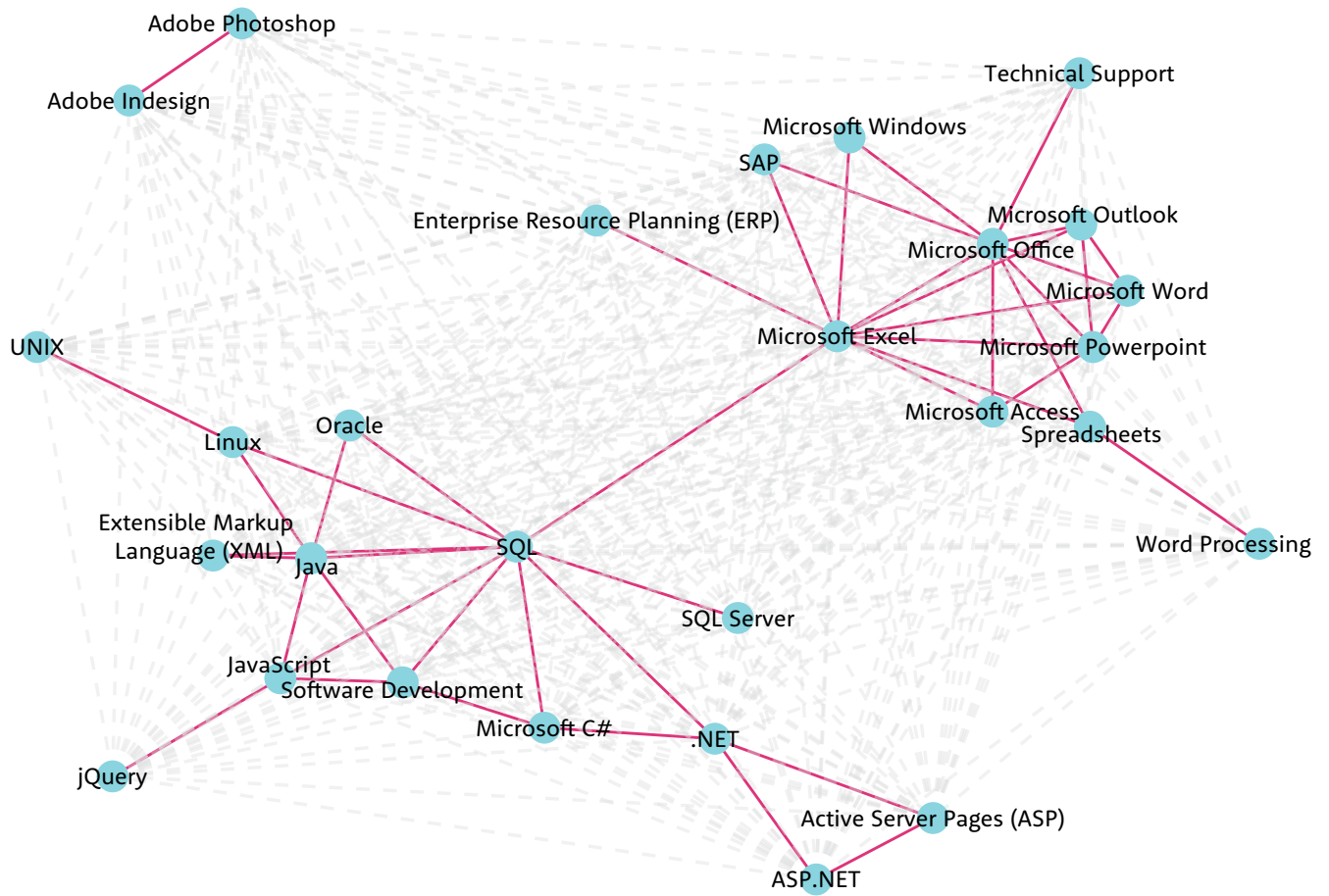
Microsoft Excel and SQL skills act as the strongest bridge between less and more digitally-intensive roles.^{29 30} Both skills sit within two distinct clusters of skills: Workforce Digital Skills, and the more digitally-intensive Software/Product Development Skills cluster. Yet the high instance of co-occurrence between these skills suggests that,

while these skills are most often requested in very distinct job contexts (with different levels of digital intensity), there are also many instances in which an employer asks for both Excel and SQL in the same job posting (see figure 8).

For an individual who is proficient at Excel, learning SQL may be an effective starting place if they are looking to break into a more digitally-intensive role — although additional credential and skill upgrading may be required. Similarly, an individual working in a more digitally-intensive role who is familiar with SQL could transfer that skill into a variety of other roles.

Figure 8

Excel and SQL connect general workforce digital skills to more specialized digital skills



Source: Author Calculations

Note: Highlighted Connections Represent the Top Connections Between Skills.

Occupational examples

Business Intelligence Analysts

Produce financial and market intelligence by querying data repositories and generating periodic reports. Devise methods for identifying data patterns and trends in available information sources.

- + In 2016, there were around **87,000** Business Intelligence Analysts in Canada.
- + Between 2012 and 2018, there were **25,829** job postings for this occupation.

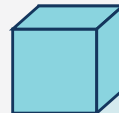
21.8% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Business Systems Analysis
- Project Management
- Information Gathering

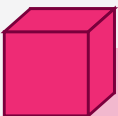
14.4% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Problem Solving
- Meeting Deadlines

18.6% Workforce Digital Skills



Skills in a typical job posting

- Data Analysis
- Data Modeling
- Microsoft Excel

13.1% Data Skills



Skills in a typical job posting

- Tableau
- Data Warehousing

17.2% Communications Skills



Skills in a typical job posting

- Written Communication
- Business Planning

11.5% Software/Product Development Skills



Skills in a typical job posting

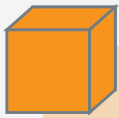
- SQL
- UNIX Shell

Database Administrators

Administer, test, and implement computer databases, applying knowledge of database management systems. Coordinate changes to computer databases. May plan, coordinate, and implement security measures to safeguard computer databases.

- + In 2016, there were **22,710** Database Administrators in Canada.
- + Between 2012 and 2018, there were **21,737** job postings for this occupation.

26.1% Software/Product Development Skills



Skills in a typical job posting

- UNIS Shell
- MySQL
- Red Hat Linux
- Sphinx

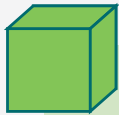
10.9% Skills associated with having a bachelor's degree or more



Skills in a typical job posting

- Analytical Skills
- Project Management

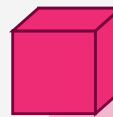
17.5% Data Skills



Skills in a typical job posting

- Database Architecture
- Database Management
- Database Design

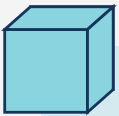
10.1% Workforce Digital Skills



Skills in a typical job posting

- Information Systems

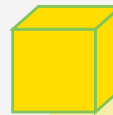
14.8% Skills associated with not having a bachelor's degree



Skills in a typical job posting

- Troubleshooting
- Communication Skills

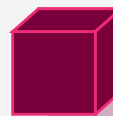
10.0% Communications Skills



Skills in a typical job posting

- Customer Relationship Management

9.9% System Infrastructure Skills



Skills in a typical job posting

- Solaris

CONCLUSION AND DISCUSSION

As the nature of work shifts, policymakers, educators, and training providers often struggle to stay abreast of evolving skills demands. We know broadly that workers will need some combination of digital and non-digital skills, such as social skills, judgment, problem-solving, and creativity.³¹ However, less is known about the specific combinations of skills employers are seeking. This lack of granularity can inhibit policymakers and educators from effectively responding to changing skills demands, and prevent workers from developing the skills that will best position them to succeed in the job market and their career.

THE DEMAND FOR DIGITAL AND NON-DIGITAL SKILLS

Using job postings data from Burning Glass, this report makes two crucial contributions to our understanding of the demand for digital and non-digital skills. First, we improve and clarify our understanding of digital skills, not as a monolithic entity, but as skills that exist along a spectrum of intensity. We also show that digital skills appear in four distinct, but connected, clusters. The definition we established and tested in this report provides a jumping-off point to further examine the demand for digital skills in the Canadian labour market. How do they change for different industries, occupations, and geographies? What additional credentials and certifications are employers looking for when they ask for digital skills? What kinds of wage premiums are attached to digital skills?

Second, we uncover the demand for digital and non-digital skills across Canada. Notably, the least digitally-intensive skills are the most widely demanded. While highly technical digital skills, such as coding, are and will likely remain a critical skill set, most workers do not require knowledge of these skills.

For most Canadians, it is more important to build a basket of general-purpose skills that includes baseline digital skills, in particular those related to using general purpose software, as well as more general soft skills pertaining to communications and interpersonal interaction, problem-solving, and general project management skills. For policy makers, educators, and training providers, this suggests that there should be a wide variety of accessible programming designed to teach Canadians general workforce digital skills, including basic data and spreadsheet skills such as Excel, along with general soft skills training.

For workers looking to move between jobs with different digital skill requirements, developing their data skills may be a good place to start. Many data skills are not only in high demand across the economy, but also appear in job postings that reflect a range of levels of digital intensity.

One area of skill upgrading that perhaps warrants more attention is between Excel and SQL. Excel is the single most in-demand digital skill, and is critical across many occupations and industries. If a worker is proficient in Excel, augmenting this knowledge with SQL skills may serve as a useful stepping stone to enter more digitally-intensive

occupations. This also suggests that when introducing workers to more advanced digital skills, programs should make constructive use of a worker's existing digital skill knowledge to allow workers to build up their skill repertoire.

Finally, in many highly technical roles, from jobs in digital media to software development, employers rarely look for digital skills in isolation. Instead, workers are expected to have some combination of technical domain knowledge, such as the ability to use a specific coding language, and a suite of soft

skills ranging from general interpersonal skills all the way to judgment, problem-solving, and project management.

For policymakers, educators, and training providers, this suggests that digital skills, while important, are rarely enough to be competitive in the labour market. Programs, such as computer science degrees or coding bootcamps, should also prepare learners for the kinds of creative, problem-solving, and team-oriented non-digital skills that employers are looking for.

A P P E N D I X A : O V E R V I E W A N D R E P R E S E N T A T I V E N E S S O F T H E D A T A

Throughout this report, we use data obtained from Burning Glass Technologies (Burning Glass). Burning Glass is a private labour market analytics company that uses web crawlers to scrape job posting level data from online job boards, recruiter websites, and business websites on the internet. The company has a database of more than one billion current and historical job postings worldwide. It is one of the most comprehensive sources of data on job openings. Burning Glass parses the raw text of job postings to extract key attributes, such as the occupational group the posting belongs to, the skill composition required, as well as qualifications and experience requested. The coding process was deemed to be more than 80 percent accurate by an independent audit conducted in 2016 for the US data.³²

But what is a job posting? A job posting is a device used by employers to find potential employees; it lists the qualifications and skills an employer desires in a candidate, as well as information about the job being hired for and about the company doing the hiring.

Importantly, job postings are used strategically by employers to not only signal needs but to target specific talent that could be a good fit for the position. Employers, as a result, may use specialized or coded language in the job description that can be interpreted easily by those with the desired background.

Furthermore, though a job posting likely reflects what employers think they need in a candidate, this may not correspond to what is actually needed at the firm, or reflect the actual day-to-day tasks performed by the employee if that job is filled.

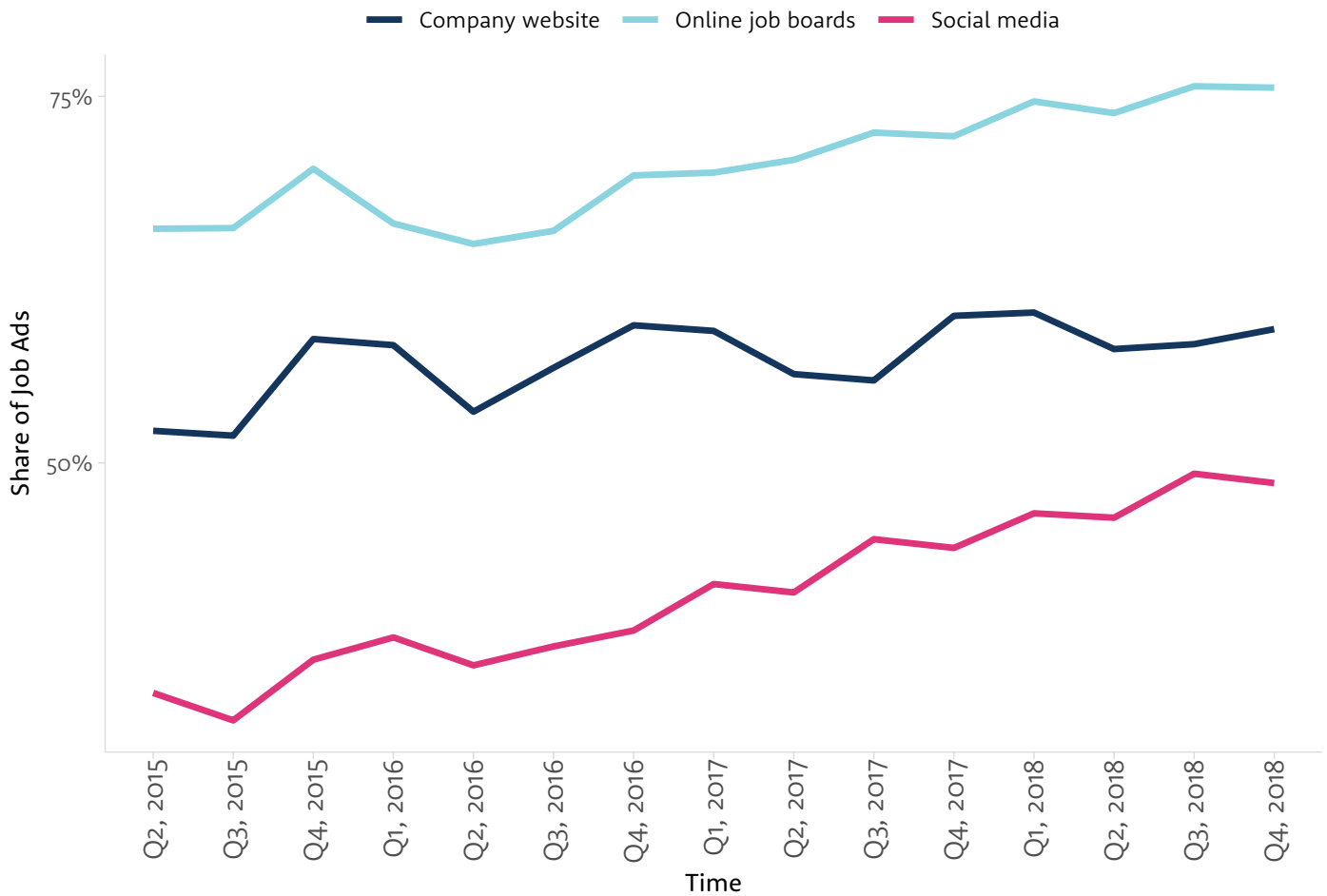
Given how job postings are generated, then, what does this represent? Firstly, job postings give us a signal about a firm's intention to hire. Though posting a job may be a relatively inexpensive process, developing a particular job description is not. As a result, a job posting represents a genuine signal of employers' intention to hire for that particular position.

Secondly, looking at job postings, and job vacancies data in general, allows us to better understand the flow of employment and the dynamics of where and how job transitions occur. This gives us a different set of insights from analyzing the stock of employment. For example, a particular occupation may have a relatively fixed stock of workers in it, but may involve short term contracts and thus a high level of dynamism in hiring and jobs being posted.

Using job postings for labour market insights is not new. Researchers have utilized newspaper job adverts as early as 1987 in the United States to understand labour dynamics.³³ However, the medium through which job advertisements have been communicated has shifted over time. Statistics Canada's Job Vacancy and Wage Survey (JVWS) shows that between 2015 and 2018, around 70 percent of vacancies were posted on an online job board, with an increasing trend. This is consistent with trends observed in the United States.³⁴ This implies that Burning Glass data coverage improves with time.

Figure A.1

Job Recruitment Strategy in Canada



Source: Job Vacancy and Wages Survey

However, this also shows that online job postings do not exhaustively cover the economy. It is then important to understand how well Burning Glass aligns with and deviates from other sources on job openings, as well as the current stock of workers

working in a particular occupation. To understand these trends, we compared the Burning Glass data sample with two main sources: the JWVS and the 2016 Canadian long form census data.

Overview of Burning Glass data

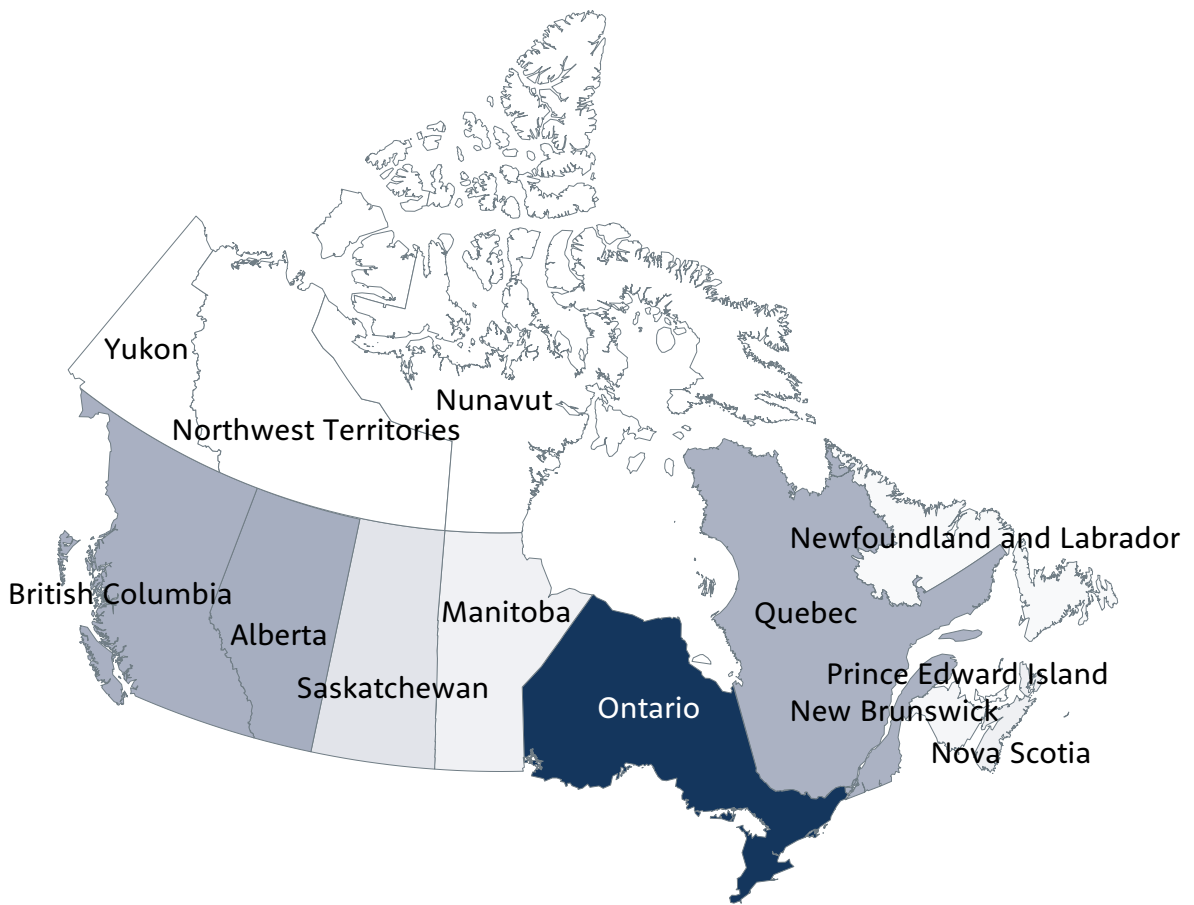
The data we analyzed for this report spans the period between January 5th, 2012 and December 31st, 2018. This represents 7,192,983 job postings in total. Job postings were collected for all 13 provinces and territories in Canada, though only postings in English were collected, due to the platform being optimized for processing English-language job postings.

The majority of job postings were concentrated in Ontario — unsurprising given the fact that Ontario is the largest province in Canada. Though Quebec is the second largest, the lack of ability to parse job data in French means that the number of jobs recorded here was also lower than the province’s overall share of employment.

On average, 85,631 postings were captured across Canada every month:

Figure A.2

Distribution of Burning Glass Job Postings by Province



Source: Burning Glass

Table A.1: Distribution of Burning Glass Job Postings by Province'

Province/Territory	Number of Job Postings (cumulative 2012-2018)	Share of Burning Glass Job Postings	Share of job postings in JWVS (Q2 2018)	Share of Employment (2019) ³⁵
British Columbia	1,071,217	14.9%	19.6%	13.5%
Ontario	2,946,740	41%	38.4%	39.0%
Manitoba	193,378	2.7%	2.8%	3.4%
Alberta	1,103,817	15.3%	10.6%	12.3%
Nova Scotia	203,508	2.8%	2.1%	2.4%
Quebec	1,044,653	14.5%	21.1%	22.8%
Saskatchewan	363,185	5%	1.9%	3%
New Brunswick	129,694	1.8%	1.7%	1.9%
Newfoundland and Labrador	85,515	1.2%	0.7%	1.2%
Northwest Territories	9,117	0.1%	0.1%	<0.1%
Yukon Territories	7,510	0.1%	0.2%	<0.1%
Prince Edward Islands	28,395	0.4%	0.4%	0.4%
Nunavut	6,254	0.1%	0.1%	<0.1%

To further examine the representativeness of Burning Glass data, we compared it to other sources of labour market information. The first source of data we consulted was the JWVS. We chose this specific dataset as it attempts to capture similar job openings data to Burning Glass.

Importantly, the JWVS captures job openings regardless of whether they are posted online or offline. However, some sample variation is inevitable in the JWVS, as it has a smaller (albeit random) sample size compared to Burning Glass.

Table A.2: Data Quality in JWVS for Different NOC Levels

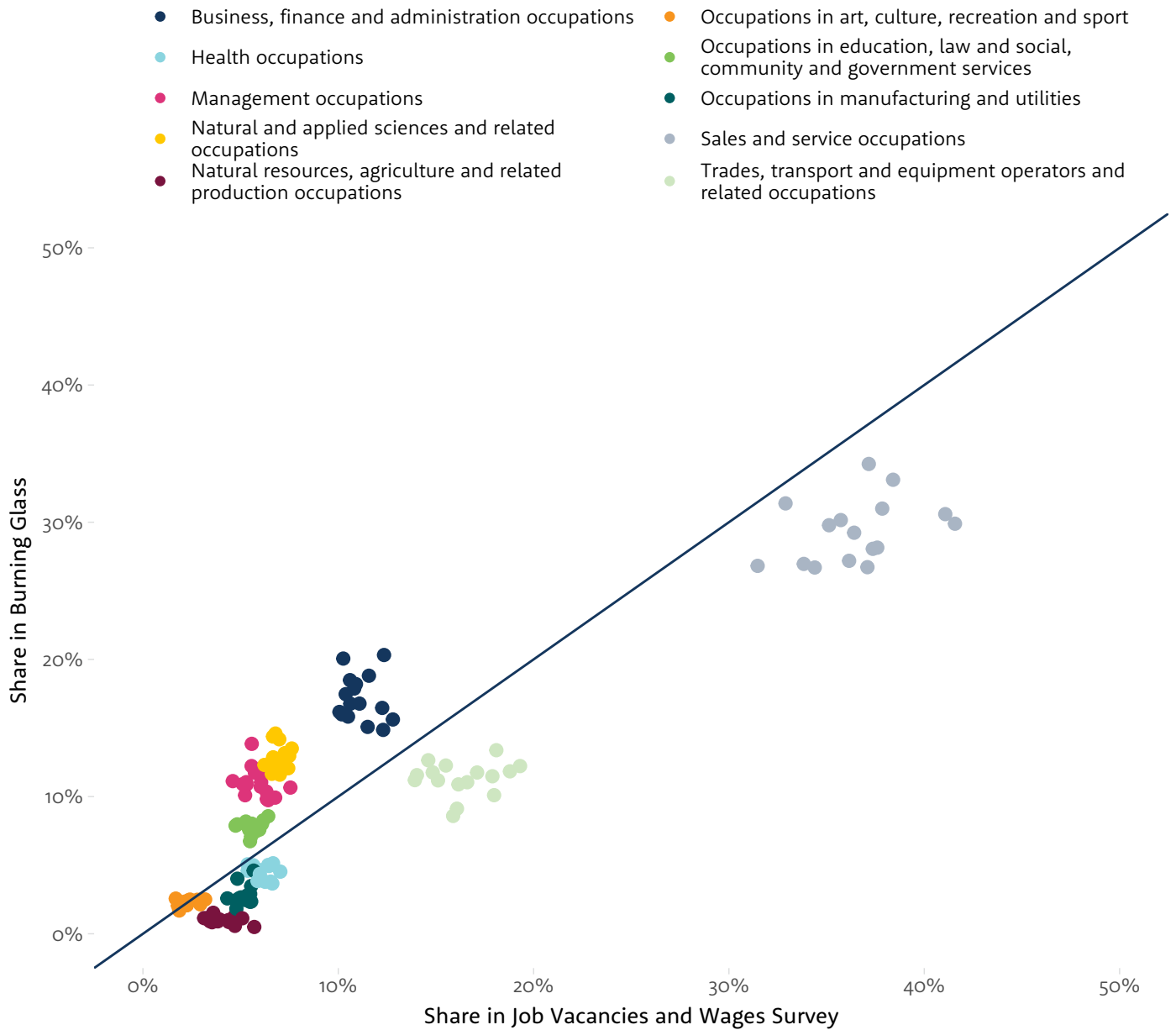
Quality	NOC-1	NOC-2	NOC-3	NOC-4
Excellent	73.1%	32.0%	4.8%	0.8%
Very Good	19.4%	48.1%	32.1%	10.2%
Good	1.3%	11.1%	25.4%	14.7%
Acceptable	6.3%	2.3%	20.9%	26.2%
Use with Caution	0.0%	4.5%	6.5%	13.6%
Too Unreliable	0.0%	1.9%	6.5%	18.5%
Suppressed	0.0%	0.0%	3.7%	14.1%
Not Applicable	0.0%	0.0%	0.1%	2.0%

The JWVS was introduced in 2015 and is collected on a quarterly basis — every January, April, July, and October. As such, we also compiled monthly job postings data captured by Burning Glass in those four months, for four years: 2015, 2016, 2017, and 2018. Specifically, we looked at the share of job postings in both Burning Glass and JWVS that came

from a particular major occupational group (NOC-1). Further disaggregation of occupational group is possible, though not advisable, as JWVS becomes less precise. The highest aggregation of NOC is the only level with a majority of data points being deemed ‘excellent’.

Figure A.3

Comparison between Burning Glass and JWWS, by Occupation



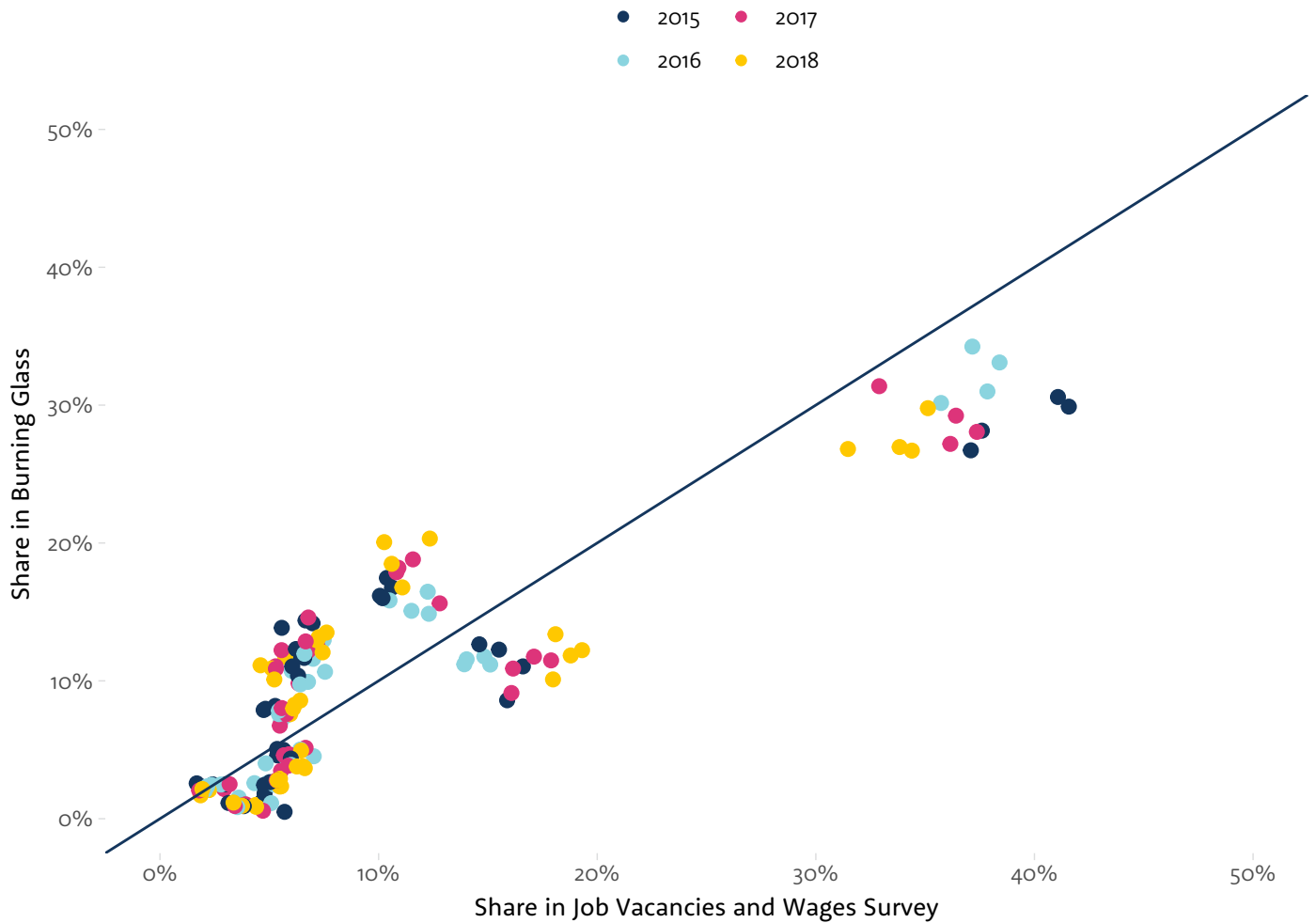
Source: Job Vacancies and Wages Survey, Burning Glass.

It can be observed that, broadly, job postings in Burning Glass match well with JWWS. There are some particular discrepancies: for example, Burning Glass has considerably less postings, in terms of proportion, from sales and service

occupations, while having a higher share of manufacturing, natural and applied sciences and related occupations, and management occupations. The correlation between the two series was 0.8775.

Figure A.4

Comparison between Burning Glass and JWWS, by Year



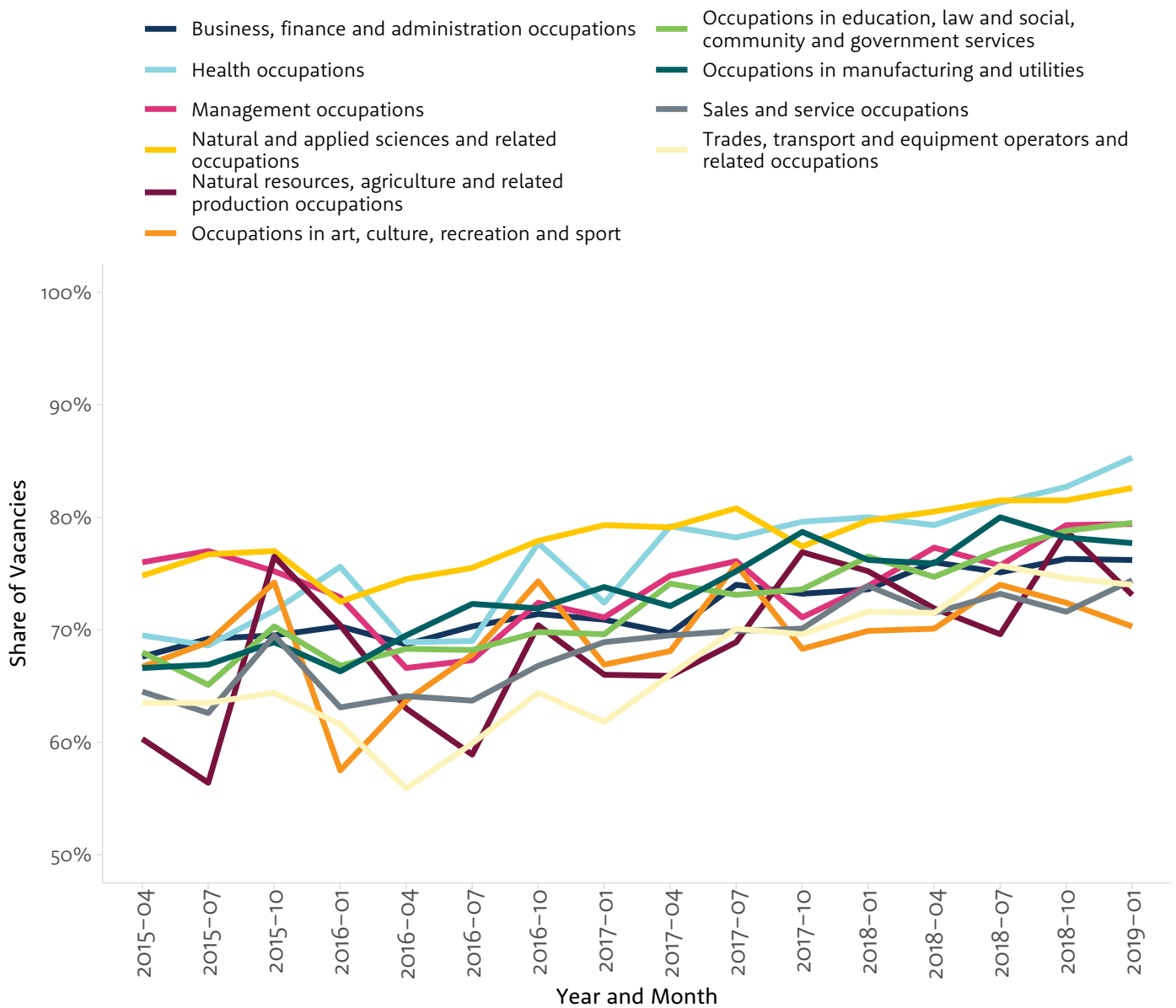
Source: Job Vacancies and Wages Survey, Burning Glass.

The deviation between the two data sources was relatively stable across the four years, while the mean of the squared differences tended to be lower in later years. 2016 had the lowest deviation between the two data sources. One potential explanation for this deviation could relate to the

change in propensity for employers to advertise job postings online. The data shows that there are substantial variations in both temporal and occupational dimensions in the share of job advertisements posted online.³⁶

Figure A.5

Change in Share of Vacancies Advertised Online, by Occupation



Source: Job Vacancies and Wages Survey

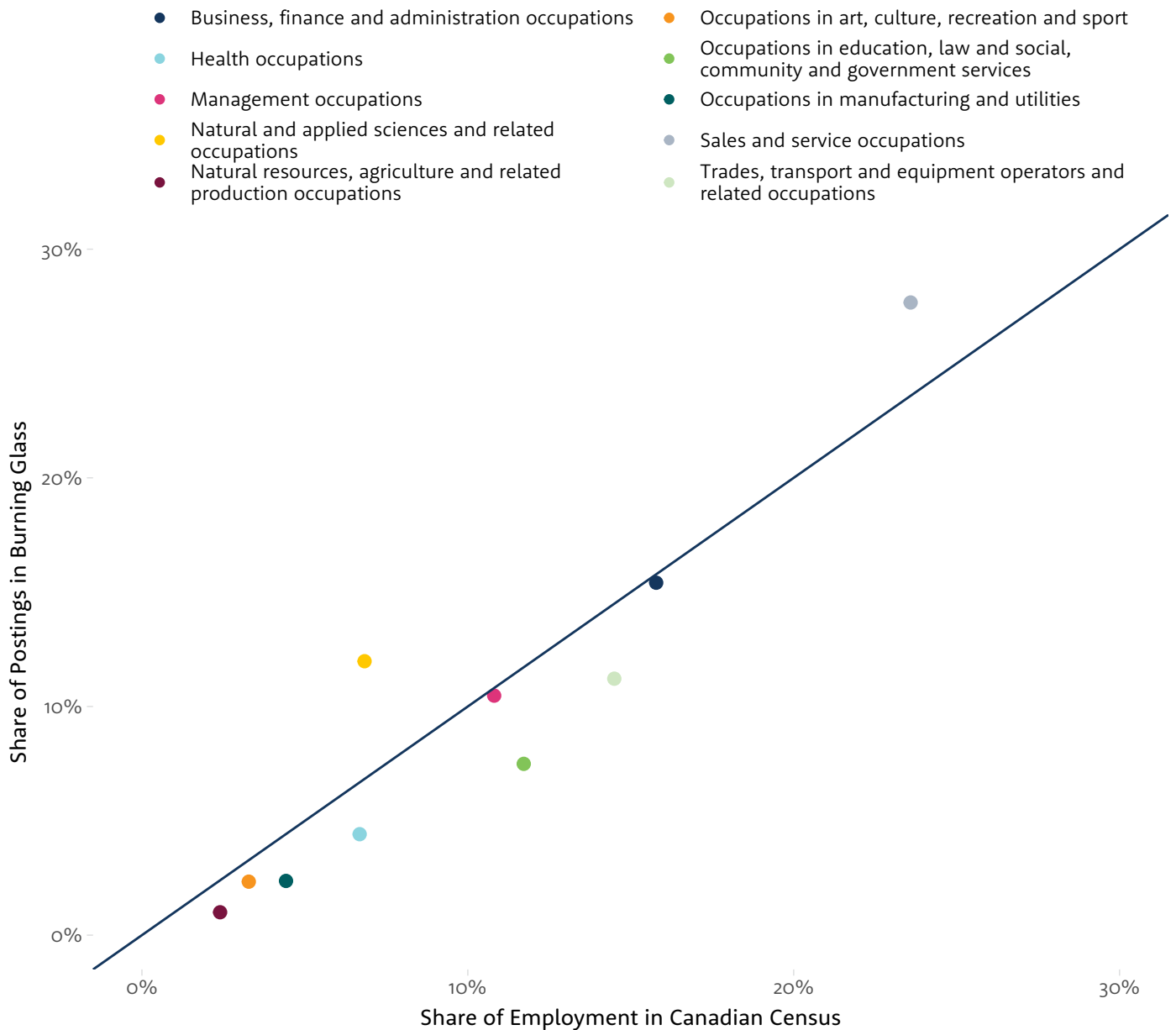
What this implies for Burning Glass’s data is that temporal variation in job postings for an occupation can be decomposed into two main forces: increased use of online job advertisements for that occupation, and increased demand for that occupation overall.³⁷

Another comparison that can characterize Burning Glass’s ability to summarize labour conditions is in understanding how well it matches up to the

current stock of workers. When we compared the postings by the share of workers working in major occupations in 2015 (as collected by the 2016 census), it was clear that Burning Glass postings have higher shares of posting in sales and service occupations,³⁸ as well as natural and applied sciences and related occupations. Apart from that, the two sources are remarkably similar.

Figure A.6

Comparison Between Burning Glass and the 2016 Census, by Occupation



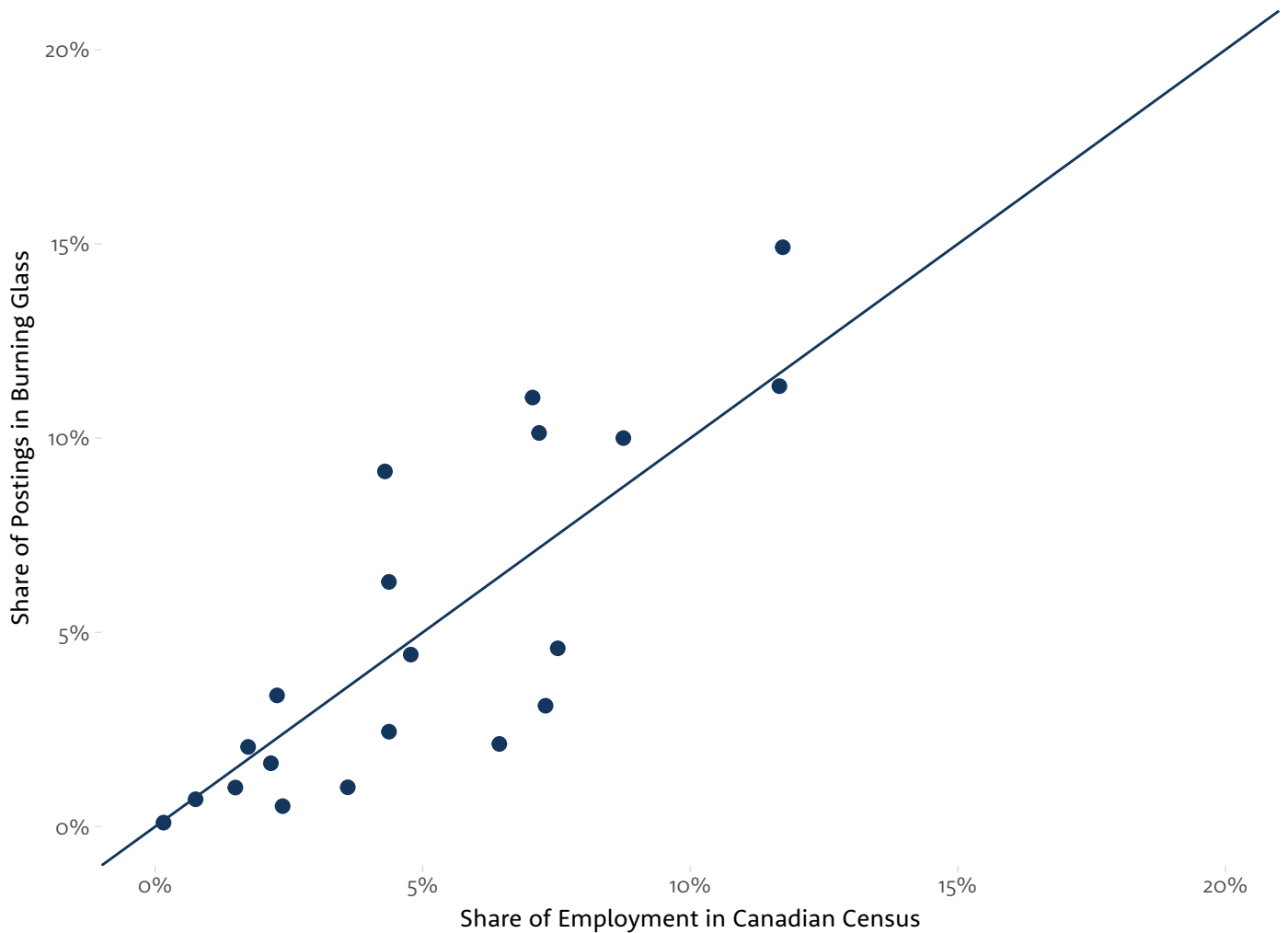
Source: Burning Glass, and 2016 Canadian Census

When we compared the share of postings that came from a particular industry in Burning Glass to the share of workers in a particular industry across Canada (again, for 2015, using the 2016 Canadian census), it was clear that, on average, Burning Glass is a fairly good representation of the broader labour market. The correlation in this case was 0.824.

When examining representativeness, we also wanted to examine whether job postings disproportionately represent less- or more-skilled workers. As a proxy, we used the education credentials asked for by employers in Burning Glass job postings data, and compared them to the educational attainment of individuals working in those same occupations. As a blunt instrument, we calculated the share of workers (and job postings) with a bachelor's degree or above.

Figure A.7

Comparison Between Burning Glass, and the 2016 Census, by Industry



Source: Burning Glass, and 2016 Canadian Census

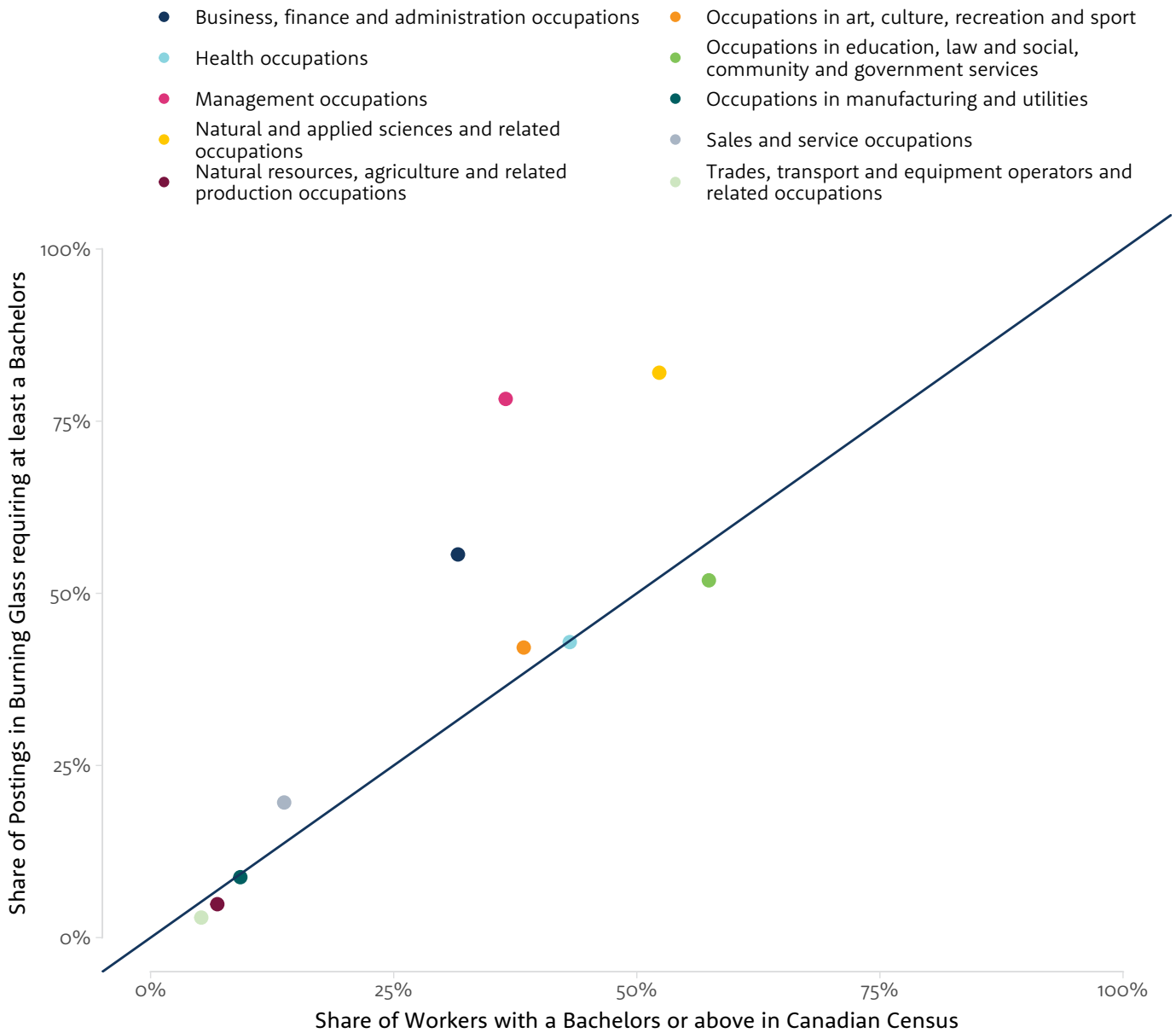
In Burning Glass, just below one third of job postings (31.3 percent) in 2015 listed degree requirements.

Looking at the distribution of degrees, the two data sources are similar across most occupational groups. Three occupational groups stand out in this comparison, all of which have a higher share of job postings asking for a bachelor's degree or above

compared to actual occupational distribution. These are management occupations, natural and applied sciences and related occupations, as well as business, finance, and administration occupations. This could reflect changing credential requirements, or the existence of internal promotion mechanisms that might not be captured in job vacancies and postings.

Figure A.8

Comparison Between Burning Glass, and the 2016 Census, by Education and Occupation



Source: Burning Glass, 2016 Canadian Census

From this series of representativeness checks, we can conclude that, overall, Burning Glass data provides a fairly good snapshot of the Canadian labour market. There are important points to consider, however, detailed below:

- + Burning Glass underrepresents job postings coming from Quebec, though this does not appear to affect its overall representativeness of the Canadian labour market.
- + Data coverage increases over time, making temporal comparisons difficult in our data.

A P P E N D I X B : D E F I N I T I O N O F D I G I T A L S K I L L S

To define digital skills, we took inspiration from the framework established in Djumalieva and Sleeman (2018), which examined the demand for digital skills in the UK using Burning Glass software markers as a starting set. They then utilized a word-embedding model to elicit other skills that are commonly listed alongside software skills to define their set of digital skills.

For this report, we started with that same set of software skills. In our Canadian sample, there were 1,753 unique software skills. We further augmented this list by manually examining all 29 skill clusters and 650 skill cluster families to identify broad clusters that identify software and digital skills. This resulted in the following clusters (highest skill hierarchy) being included in our analysis: “Information Technology”, “Analysis”, “E-Commerce”, “Web Analytics”, and “Bioinformatics”. We call these “base digital skills”.

Using occupation tech intensity score to define software+

However, over 6,200 skills (representing 48% of the skills space) were not categorized into a skill family or a skill cluster family. This group might contain software and technology skills that are important to our discussion. Additionally, as our study also focuses on identifying non-digital skills that appear alongside digital skills, any form of clustering or distance-based metric between skills may not be effective for identifying digital skills, as certain non-digital skills we want to identify as unique may be classified as a digital skill instead.

As a result, to independently identify important digital skills, we focussed on augmenting the base set of skills included in the Burning Glass taxonomy by also identifying skills that consistently show up in digitally-intensive occupations. To identify the digital intensity of an occupation, we utilized a methodology outlined in Vu, Zafar, and Lamb (2019), using the US O*Net database. Unlike in the previous report, which generated the digital intensity for Canadian National Occupation Classifications (NOCs), since Burning Glass maps directly to O*Net classifications, we generated the rankings directly for O*Net occupations.

Since each job posting was assigned a corresponding O*Net occupation, we were able to assign to each posting, and all the skills listed in each posting, the corresponding digital intensity score. We then took the average rank for each skill across all job postings. Intuitively, the resulting rank for a skill will be high if that skill is consistently listed in occupations with a high digital ranking. Conversely, the rank for a skill will be low if that skill is more likely to show up in job postings associated with occupations with low digital ranking. For example, the skill for Objective C (a programming language) is 18.75 (111th highest tech skill out of 12833 skills), whereas the skill for Companionship (a dance technique) has a rank of 822.68, being one of the lowest-ranked skills.

To examine whether our approach yields useful results, we tested the following hypothesis: the probability that a particular skill is a base digital skill (listed in one of Burning Glass’s previously defined digital skills classifications) increases

as the digital intensity ranking increases. As the construction for the Burning Glass digital skills classifications are binaries (i.e., a skill either does or does not exist within the digital skill category), we estimated the probability of a skill with a particular ranking of being a base digital skill using a logistic regression. A logistic regression estimates the conditional density function of a particular event happening. In this case, it estimates the probability that a particular skill, with a particular ranking, is a base digital skill. We expected the coefficient on the ranking to be negative.³⁹ The estimated equation shows that this is the case. More importantly, it illuminates a potential cut-off for defining digital skills, which we discuss later.

Table A.3: Regression Results

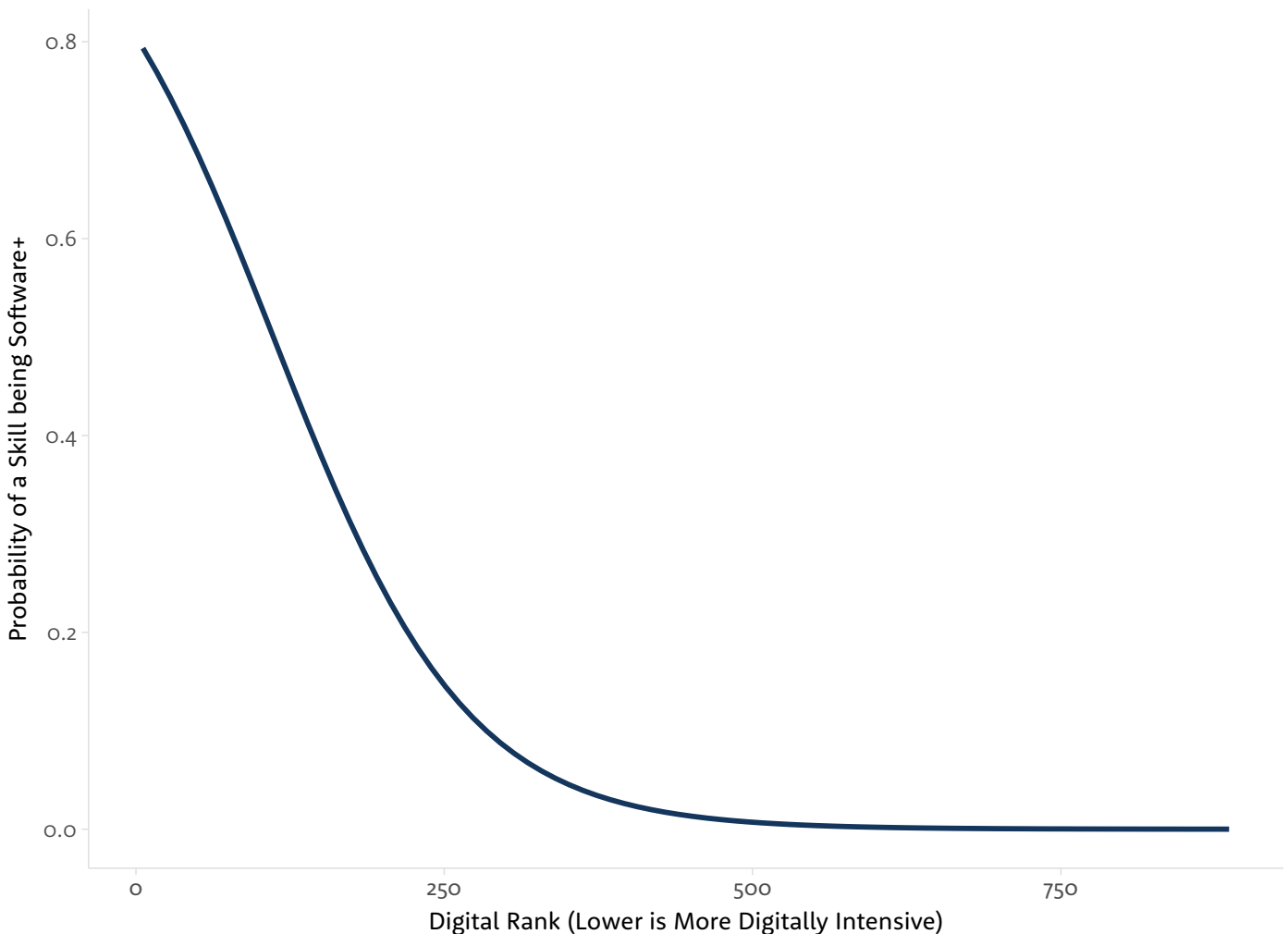
	Estimate	Z value	p-value
Intercept	1.4181*** (0.0552)	25.71	0
Digital Intensity	-0.0127*** (0.0002)	-43.97	0

Dependent variable is whether a skill is a base digital skill or not. Logistics regression using Maximum Likelihood Estimation.

Degrees of Freedom: 9,509

Figure A.9

Estimated Logistics Regression for Digital Intensity Score



Source: Author Calculations

Assumption verification

One obvious limitation of using this method is that it fails to capture digital skills that consistently show up in job postings where the associated occupations have low digital rankings. However, since Burning Glass also captures whether a skill is a software skill, we can circumvent part of this issue by also including in our definition of digital skills those that are labelled as software skills.

But there is still the challenge of classifying potential skills as digital skills that do not appear in highly digital occupations, and also do not fit within one of Burning Glass’s base digital or software skills. For this method to be able to identify most digital skills, the following identification assumption must hold: when a digital skill is listed for a job posting, the likelihood of that digital skill being labeled as software increases as the digital intensity of an occupation declines. This assumption is motivated by previous research from Huynh, Do (2017) who distinguish between baseline digital skills, workforce digital skills, and professional digital skills. The more digitally-intensive the skill, the more one is required to not just be proficient in a specific software, but to be well-versed in computational thinking.

To test this assumption, we took the base set of 1,753 software skills and combined it with 1,578 base digital skills, and estimated the conditional probability of a skill in a job posting being a software skill⁴⁰ and how it changed with the tech intensity ranking of a job posting. Using Bayes’ rule,⁴¹ this simply became:

$$\frac{P(\text{software})}{P(\text{digital})}$$

We then estimated the equation:

$$\frac{P(\text{software})}{P(\text{digital})} = \beta_0 + \beta_1 h_1 + \epsilon_i$$

Where h is the harmonic rank or digital intensity of a particular occupation (which varies at the occupation level), and the error term varies at the individual job postings level. As the ranking

increased for less digitally-intensive occupations, we expected the coefficient on the ranking to be positive. In addition, there is no reason to believe in a homoskedastic error structure here (as the variance of the probability may vary according to the tech intensity of an occupation), so we computed heteroskedasticity-robust standard errors for our estimate:

Table A.4: Regression Results

	Estimate	t value	p-value
Intercept	6.504×10 ⁻¹ *** (3.946×10 ⁻⁴)	1648	0
Digital Intensity	2.419×10 ⁻⁴ *** (1.102×10 ⁻⁶)	219.5	0

Dependent variable is the conditional probability of a digital skill in a job posting being a software, conditional on it being a digital skill. Linear Probability model using Ordinary Least Squares. Standard errors are heteroskedasticity-robust.

Degrees of Freedom: 2,252,332
R²:0.021
F-statistics: 4.82×10⁴

The estimate shows that a positive relationship exists, supporting the validity of our approach in identifying the right set of skills. Even if some important digital skills were not captured using this methodology, the method we developed in identifying hybrid jobs, which involves distance-based algorithms or clustering-type algorithms, should be able to identify the residual digital skills. For robustness, we also tested some common non-linear specifications, none of which invalidated this assumption in the effective range of the function [0,1].

Software+ as a definition of digital skills

Finally, we discuss the cut-off point we propose in choosing digital skills. The central tension in choosing the cut-off points for our definition of digital skills was in maximizing the number of unidentified digital skills being identified, while minimizing the number of non-digital skills being misclassified as a digital skill. As our method involved choosing a single cut-off point, the two were in direct conflict. We posit several plausible cut-off points, and discuss the value of each:

1. **The point where the estimated probability of a skill being a base digital skill is 50 percent.** The first cut-off point we propose is the digital intensity score, where roughly half of the skills present are not included in the base digital skills. For our sample, this occurs between rank 109 and 110. This means that we will end up with 1,113 additional skills being identified as digital skills, for a total of 3,651 digital skills.
2. **The point where the rate of change in the slope of the estimated function becomes increasingly negative.** In our sample, this point lies at around rank 213 and 214. This will identify 2,519 additional digital skills, for a total of 5,037 digital skills.⁴²

For our study, we erred on the side of caution, where the number of additional skills identified did not exceed the number of skills already classified as base digital skills. A spot check also confirmed these results. Most skills that fell between the digital intensity rank of 109 and 110 could be reasonably classified as digital skills, while skills that fell around rank 213 were much less likely to be clearly digital skills. We chose these cut-offs as our definitions.

Table A.5: Skills Around the Strict Cut-off

Skill	Score
Bitcoin	109.59
Cognitive Science	109.64
Change data capture	109.68
General Packet Radio Service (GPRS)	109.68
Global Organizational Development	109.69
Network Installation	109.69
Quick Test Professional (QTP)	109.7
NOVELL	109.7
Engineering Design	109.71
Clinical Trial Progress Monitoring	109.71
Engineering Design and Installation	109.73
Raspberry Pi	109.80
Risk Based Testing	109.9
Group policy	109.97
Enzyme Function	110.02
Efficiency Estimation	110.05
Medical Device Design	110.05
Joomla	110.077
Rapid Prototyping	110.087
Sustainable Engineering	110.11

Table A.6: Skills Around the Generous Cut-off

Skill	Score
Biomedical Engineering	213.45
Facility and Site Construction Layout	213.47
Virtual Agents	213.48
Cell Phone Industry Knowledge	213.54
Corrective Action Planning	213.59
Mortgage-Backed Security (MBS)	213.62
Multiple Regression	213.69
RNA Isolation	213.69
Blogger	213.8
Site Assessments	213.8
Liquidity Risk Models	213.84
Long-Only	213.91
Open End Wrenches	214.05
Restoration Strategy	214.14
PPM Tools	214.2
Electrical Diagrams / Schematics	214.28
Production Part Approval Process (PPAP)	214.3
Bill Preparation	214.34
Frozen Shoulder	214.43
Fit/gap analysis	214.48

We then took a random sample of 100 skills from the taxonomy, hand-classified them into software+ skills, and assessed type 1 and type 2 errors using the two threshold heuristics. In the stricter threshold, 29 out of 100 skills were identified as software+ skills. The hand classification and the strict threshold agreed 92 times. There were seven instances where the hand classification classified a skill as software+ and the stricter threshold did not. There was one instance where the hand classification did not classify a skill as software+ and the stricter threshold did.

Type 1 error: 20%; type 2 error: 1.5%

Under the second (more generous) threshold, 37 skills were identified to be software+. The hand classification and the second threshold agreed 92 times. There were three instances where the hand classification classified a skill as software+ and the wider threshold did not. There were five instances where the hand classification did not classify a skill as software+, while the threshold categorized the skill as software+.

Type 1 error: 8.5%; type 2 error: 7.7%



APPENDIX C: NETWORK ANALYTICAL FRAMEWORK

The central focus of this report is identifying how skills interact with each other. In particular, we are interested in how digital skills interact with non-digital skills. Our contribution to this literature involves conceptualizing skills and job postings as a network (or, more formally, a graph). This is a natural conceptualization given Burning Glass's data, where different skills are connected to each other by appearing together in the same job posting. Our purpose, then, is to understand the patterns of communities that might exist within these skills.

Within a graph theory framework, there are many community-detection algorithms, each with different graph metrics as the objective function. We must prioritize the most desirable community characteristics for our research purposes. For our purposes, it is important to distinguish between two types of skills: general skills and specialized skills. General skills are skills such as 'communications' and 'leadership'. Almost all job postings contain a set of general skills, as these skills are applicable across most occupations. Specific skills are those that appear less often, and are usually confined to specific occupational groups or tasks. As our study focuses on digital skills, many of which are non-general, we ideally would place less weight on general skills in defining skills clusters. In addition, general skills should not form an important role within any cluster, and should ideally connect different clusters together.

Given these constraints, some community detection algorithms, such as label propagation, where nodes with large weights have the most influence in determining the community, were ruled out. We instead focused on two particular graph clustering techniques: modularity-based and edge-betweenness-based.

Given a community structure, the modularity of a graph is, intuitively, how well-connected nodes within each community are compared to the likelihood of these nodes connecting if such connections are formed randomly. Modularity-based algorithms in community detection are a class of algorithm that divides a network into communities that maximize modularity in the network. Many popular and well-implemented versions of these algorithms operate on a hierarchical basis: each node in the network starts in its own community and is iteratively aggregated, until all nodes belong to the same community. Communities that when grouped together increase global modularity the most are grouped, and the aggregation level that maximizes the modularity is then chosen.

$$Q = \frac{1}{2m} \sum_{vw} \left[A_{vw} - \frac{k_v k_w}{2m} \right] \delta(c_v, c_w)$$

Modularity of a Network

Where Q is the modularity

A_{vw} is the adjacency indicator for nodes v and w

k_i is the degree (sum of weights of edges connected to) of node i

m is the number of nodes in the network

$\delta(c_v, c_w)$ is a function equal to 1 when v and w belongs to the same community, otherwise 0.

$$g(e) = \sum_{s \neq e \neq t} \frac{\sigma_{st}(e)}{\sigma_{st}}$$

Betweenness Centrality of an Edge

Where $g(e)$ is the betweenness centrality of edge e

σ_{st} is the number of shortest paths that connect between nodes s and t

$\sigma_{st}(e)$ is the number of shortest paths that connect between nodes s and t that go through edge e

As a result, these algorithms tend to group nodes with lower degrees first, and thus have a lower chance of being connected to each other in a

random network. Nodes with large degrees, or nodes with the highest chance of being connected to each other in a random network (which, in our context, corresponds to basic skills), do not act as pivotal nodes in defining a community. However, as modularity improves greatly with a higher number of edges in the network than expected, these large nodes are more likely to have many ‘within-community’ edges, as opposed to ‘across-community’ edges. This is due to the fact that any connection to nodes outside the community from these central nodes will not contribute toward the global modularity, while non-connections within the same community will hurt global modularity.

Edge-betweenness algorithms rely on detecting community structures through another graph metric: betweenness centrality. Betweenness centrality is measured for each edge, where edges that are on the highest number of shortest paths connecting any two nodes will have the highest betweenness. Intuitively, if such an edge is removed, the graph will be more divided than it was previously. After removing enough edges with high betweenness, the graph will break into two distinct communities, then three; eventually, each node will occupy its own community (after all edges have been deleted).

Finding community structure using edge-betweenness centrality is the reverse of a modularity-based algorithm, where edges are removed from the main graph until every node belongs to its own community. Such an algorithm, then, will likely delete the edges associated with nodes with a high degree (in our context, basic skills) first, where these nodes then act as nodes that connect between communities. However, as these nodes are likely to be isolated first, they will only determine initial community divisions, and not an inherent community structure.

However, edge-betweenness algorithms are

computationally demanding, and do not scale to a large number of nodes. For this reason, we favoured modularity-based algorithms for this report.

Due to the graph having a vastly higher number of job nodes than skill nodes, when running a community detection algorithm, a graph that aggregates the bipartite network into a network just involving skills was beneficial for our purpose. An important issue that is worth discussing involves how to manage weights of edges between skills. In the full bipartite network, skills can be connected multiple times through multiple jobs, and, intuitively, edges between skills connected by many jobs should receive higher weights than edges between skills connected by fewer jobs. However, our choice of weights and their relative importance will also affect our choice of the objective function used in any clustering or community detection algorithm, so a discussion on ideal weights is warranted here.

In this quadrant of analytics, an ideal weight would, as stated in the previous paragraph, put more weights onto edges where skills co-occur more often. However, in our full sample, the edge with the highest weight is 804,756 times stronger than the edges with the lowest weight. More importantly, the edges at the 75th percentile are six times higher than the edges at the 25th percentile, highlighting a huge difference between co-occurrences. We likely want to preserve the severity of this disparity.

In transforming these weights, two considerations should be given: whether to preserve the ordinal nature of these weights, and how to transform the cardinal nature of these weights. The first question surrounding ordinality is the most important, as altering the ordering of edge weights will change the graph structure, and any such decision needs to be made with thoughtful consideration. We

Table A.7: Summary Statistics of Counts of Skills

Minimum	1st Quadrant	Median	Mean	3rd Quadrant	Maximum
1	2	5	100.2	18	80475



should only consider alternating the ordinality of the weights if we believe that weights based on the number of co-occurrences have fundamental flaws in representing the structure of how skills are related to each other.

One such flaw can relate to average job length of an occupation, given the data we are currently considering. For example, jobs in some occupations tend to be short-term in nature (sales associates, for example), due to both employee and employer reasons. In these instances, occupations with high turnover will likely post job openings more frequently, increasing the instances where two skills in that occupation co-occur (as we expect job postings for a similar, or, in some circumstances, the exact same role, to be similar). However, in Appendix A, when we explore the representativeness of Burning Glass’s sample, we learn that the difference between the share of postings and the number of people working in those occupations is not particularly high (even in occupations where we expect there to be a lot of employment flow, such as sales and service occupations), negating these concerns.

One of the more intuitive ways that we can rescale these weights is by normalizing them. However, given the structure of these weights, assuming a normal distribution in re-weighting is not prudent (due to the inherent lower bound of 0 in the number of possible co-occurrences). Given these considerations, we chose not to re-weight the edges in analyzing our network.

Aggregating job postings at the occupation level

After we implemented the clustering algorithms on the skills network, we ended up with eight distinct communities of skills (characterized in the main text). The next step of the analysis was in proposing methods to translate insights gained from partitioning skills into these eight clusters onto job postings. With almost six million nodes, the full jobs space network is large and implies high levels of computational complexity, especially for algorithms that require the full adjacency matrix in assigning nodes to communities.

Though we attempted to implement a community detection algorithm for the full network using several different implementations (on a variety of different data structures), performing analytics on the full network was deemed impractical.

As a result, we decided to aggregate job postings at the O*Net Occupation level, where job postings associated with a particular O*Net occupation were aggregated, at the skills level and at the skill community level. In particular, we aimed to characterize a “representative” job posting for each of the almost 1,000 occupational groups. This approach, though useful, has several disadvantages. The main disadvantage of following such an approach is that we take the occupational partition as a given, and may potentially miss distinct occupational groups that could be identified in a skills sense, as roles in this distinct group may be distributed across several defined occupational groups.

To implement our analysis, however, we calculated, for each skill, the probability of that skill showing up in a job posting for a particular occupation using the full data. We then aggregated the individual skill probability at the skill community level. As a result, we generated the share of skills belonging to a particular community in an occupation. As a final step of our implementation, we calculated the average number of skills listed for each occupation, and calculated the implied number of skills in such a “representative job posting” belonging to each skill community.

We also used the probability that each skill shows up in a job posting to generate a hypothetical job posting for some characterized occupations.

Finally, we defined an occupation’s **hybridness** by measuring the variance of shares of skills that came from eight skill clusters (four digital and four non-digital) for each occupation. Intuitively, the most hybrid occupation will have the lowest variance in how skills are distributed across different skill clusters (as no single skill cluster will dominate skill listings from one domain).

APPENDIX D: NON-DIGITAL SKILLS CLUSTERS

Using a similar methodology, we applied the community detection algorithms to non-digital skills. This allowed us to identify four broad clusters of non-digital skills in our data:

- 1. Skills associated with having a bachelor's degree:** This skill cluster consisted of 2,755 unique skills, and included specialized skills and knowledge that span domains and are typically associated with workers holding a bachelor's degree or higher. Prominent skills included in the cluster were budgeting (490,923 mentions), project management (398,143 mentions), change management (90,794 mentions), mechanical engineering (44,394 mentions), economics (42,461 mentions), and chemistry (25,839 mentions).
- 2. Skills associated with not having a bachelor's degree:** This skill cluster consisted of 1,745 unique skills commonly utilized in work associated with less formal education, such as the trades, manufacturing, personal services, and administrative functions. Many skills in this cluster are those commonly thought of as more routine-oriented skills, which are more susceptible to automation. However, also included in this cluster were many specialized, non-routine manual skills. Prominent skills included communications skills (2,208,324 mentions), repair (447,334 mentions), administrative support (274,119 mentions), machinery (120,648 mentions), childcare (93,800 mentions), and welding (92,749 mentions).
- 3. Communications, marketing, and public relations skills:** This skill cluster consisted of 1,627 unique skills primarily related to communications and marketing for a specific business, product, and/or service for external and internal stakeholders. Some prominent skills in this cluster included teamwork/collaboration (1,044,326 mentions), customer service (989,886 mentions), sales (784,899 mentions), written communications (369,190 mentions), and bilingual abilities (295,406 mentions).
- 4. Healthcare and medicine skills:** This skill cluster consisted of 3,065 skills pertaining to healthcare and human services. Prominent skills in this cluster included those related to patient care (71,458 mentions), mental health (51,833 mentions), social services (40,150 mentions), public health and safety (36,176 mentions), and long-term care (33,605 mentions).

In particular, the names assigned to the first two clusters were guided by a high level of association between credential requirements (listing a bachelor's degree as a minimum requirement or not) associated with job postings that have a higher share of skills coming from each of the two clusters. We tested such an association in a linear probability setting and a logistics setting, obtaining similar results.

Table A.8: Regression Results

	Estimate	p-value
Intercept	0.94 *** (4.3×10 ⁻⁴)	0
Share of skills associated with not having a bachelor's degree	-1.00 *** (8.6×10 ⁻⁴)	0

Dependent variable is a dummy variable indicating whether a job posting lists at least a bachelor's degree as a minimum requirement. Linear Probability model using Ordinary Least Squares.
Degrees of Freedom: 2,089,791

R²:0.021

F-statistics: 1.46×10⁶

Table A.9: Regression Results

	Estimate	p-value
Intercept	2.42 *** (0.003)	0
Share of skills associated with not having a bachelor's degree	-6.03 *** (0.008)	0

Dependent variable is a dummy variable indicating whether a job posting lists at least a bachelor's degree as a minimum requirement. Logistics Regression using Maximum Likelihood Estimation.
Degrees of Freedom: 2,089,791

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27. This may be the result of their being no real leading web design software, as well as the language of web design (html, php, javascript) being open-sourced. At the same time, it may also reflect employer's assumptions that candidates who are proficient in web development, are also able to use or learn the specific tools and languages employed in their company.
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36. As before, the share used here is restricted to the share of job advertisements advertised on "online job boards" which is a lower bound estimate of the share of job ads advertised online overall.
37. Following Cortes, Jaimovich, Siu (2018), we can theoretically decompose the change in the number of job ads captured into those component parts. However, we lack reliable sources of data on both the probability that a job vacancy for a particular occupation is advertised online (due to data quality issues associated with the JWVS), in addition to the JWVS not being available between 2012 and 2014. As a result, we refrain from interpreting temporal changes in the number of job ads in Burning Glass.

38. Likely representing the velocity within these occupations, especially when this insight is combined from the under-representation of Burning Glass posting compared to JVWS for this occupation.
39. For this regression, we also restrict the skills we test into skills that were mentioned at least 18 times in all job postings - this allows for reduction of bias in considering very rare skills that may have a biased estimate of ranking. 18 times was chosen as it is the first quadrant of the distribution of number of times skills are mentioned.
40. Digital skill as used here includes both software and the base tech skills.
41. The conditional probability of a skill being digital conditional on it being software is 1, as we defined digital as being inclusive of both software and base tech skills.
42. For exactness, we found the point at which the third derivative of the likelihood function is 0.

