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How Far Can Your Skills Take You?

Understanding Skill Demand Changes Due to Occupational Shifts and the Transferability of Workers across Occupations.

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Labor Markets and Social Security Division

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EXECUTIVE SUMMARY

What if you had the information to identify the fastest growing jobs in your country, or even in your hometown, and the skills you need to learn to get hired in them? And what if this data could also help you decide which jobs you could most easily transfer to with just the skills you have today should you want a career change or if your current job might be soon automated?

Obtaining the information to answer these questions is a primary concern for policy makers, educators, students and workers everywhere at a time where the exponential growth of digital technologies, combined with the rapid development and deployment of robotics, artificial intelligence, the Internet of Things, and new platform technologies like LinkedIn, is accelerating the pace of technological change and creating important shifts in the workforce.

Obtaining better and timelier insights into the changing demand for skills and occupations has become a pressing challenge for all countries. However, despite a global debate about the future of work and the changing demand for skills, few studies have been able to capture skills-level data in a way that is dynamic, cost-effective, and reflective of the different markets, industries, and occupations that characterize different geographic localities.

In this paper, we provide new evidence to characterize changes in the demand for skills associated with shifts in occupations for a sample of 10 of the 20 G20 countries, using information available from LinkedIn profiles as a new and unique source of dynamic labor market data on occupations and skills. A unique feature of LinkedIn's data is the availability of granular measures of skill importance by country and occupation. This data allows us to examine how similar occupations may differ in their skills composition across different countries, and to measure the corresponding shifts in skill demand associated with changes in occupations for each locality. While the results are only representative of the subset of workers with LinkedIn profiles, they provide an important perspective on an increasing, and arguably very relevant, portion of the labor market.

A second aspect we tackle in this paper is the degree of transferability of workers across declining and emerging occupations. Understanding the transferability of skills is one of the most promising areas of analysis available through LinkedIn data. Throughout history, the development and expansion of new tasks and occupations have helped to outweigh job losses caused by waves of automation. However, this expansion can be slowed—and transitions be more costly--if recent graduates and/or workers who lost their jobs due to automation do not have the required skills to perform these new tasks or occupations. Possessing and promoting more transferable skills—i.e., those skills that are important to and shared across different occupations—may help individuals to better withstand labor market disruptions in a dynamic digital economy.

In this paper, we assess the transferability of workers employed in declining occupations to expanding portions of the economy as a first step in identifying the set of policies that may be needed to accelerate reallocation and economic adjustment, and to create more resilient learning and labor pathways for individuals. We leverage LinkedIn's granular skills data to create a distance measure that estimates how close two occupations are based on the skills that workers in those two occupations share. Potential uses of this analysis are identifying those occupations into which workers in declining occupations can transfer, identifying alternative career paths for workers wishing to switch occupations, and identifying transitions with high potential for employment growth.

Our analysis yielded several key conclusions and recommendations:

Across all examined countries, tech-related occupations and advanced digital skills are on the rise. Occupations like software developers and advanced digital skills like web development and software and web development tools are on the rise. Education and training providers must adjust their curriculums and supply of courses to ensure that learners are acquiring a command of the specific tools that are most in demand and generate professionals who can meet this growing demand. This may imply shifting some of resources from administration/management courses, toward courses that teach advanced digital skills.

People-centric roles are also growing. Many of these occupations are high skill and have increasingly important digitally oriented components but also require high levels of social intelligence to gauge and elicit people's reactions and to make high-level decisions from complex information. At the same time, lower skill service-oriented and caretaker occupations are also emerging in several countries. All of these appear to be the least likely occupations to be automated.

Countries with more connected networks of occupations may have a better chance of helping workers to transition out of declining occupations. Our results showed that in countries where occupations are closely related, workers in declining occupations have a wider array of options. These results also hold when analyzing the occupational transitions that yield the highest gains in hiring rates. Identifying how connected occupations are requires access to granular data for skills and occupations to construct measures of occupational relatedness. Fortunately, these data are becoming readily available to policymakers.

However, the analysis presented here needs to be interpreted with care. Occupations and skills are self-reported by members. Not all skills reported by members may be required or needed by employers. Similarly, members may report the skills they think employers look for and underreport skills that they consider less important. This may be the reason why soft skills appear less important in this study than in other recent studies.

Finally, the results of our analysis illustrate that **data reported by members of professional networks and job search platforms such as LinkedIn can be valuable new sources of information with which to assess rapidly changing skills demands and to increase countries´ adjustment capabilities.** However, these alternative data sources complement rather than replace traditional sources of workforce data, such as censuses, household and employer surveys, and administrative data like education, tax, social security, and unemployment records. Investments in modern labor market information systems are necessary to facilitate the interoperability, sharing and dissemination of different sources and types of data. This intelligence can be shared with a range of stakeholders, including parents and students, workers, employers, policymakers, and education and training providers to 1) generate a more complete and timely picture of the labor market; and 2) facilitate a more rapid and informed adjustment of workforce development policies and programs.

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INTRODUCTION

The accelerated pace of technological change is creating important shifts in the workforce.

This paper provides new evidence to characterize changes in the demand for skills associated with shifts in occupations for a sample of 10 of the G20 countries. It uses information available from LinkedIn profiles as a new and unique source of dynamic labor market data on occupations and skills.

The exponential growth of digital technologies, combined with the rapid development and deployment of robotics, artificial intelligence (AI), the Internet of Things, and new platform technologies, is accelerating the pace of technological change and creating important shifts in the workforce. The rapid growth and deployment of new technologies is advancing the potential of automation and shifting the demand for some occupations relative to others. Several studies show that in the developed world, occupations composed mainly of repetitive tasks are increasingly being automated, and the demand for workers in those occupations is declining. In contrast, occupations in which workers perform mostly non-repetitive tasks, and therefore are not easily automatable, are growing over time (OECD 2018). Occupational shifts, in turn, increase the demand for certain skills relative to others.

This paper provides new evidence to characterize changes in the demand for skills associated with shifts in occupations in a sample of 10 of the G20 countries, using information available from LinkedIn profiles as a new and unique source of dynamic labor market data on occupations and skills. While these results are only representative of the subset of workers with LinkedIn profiles, it provides an important perspective on an increasing portion of the labor market. A unique feature of LinkedIn's data is the availability of granular measures of skill importance by occupation and country.

A second aspect we investigate in this paper is the degree of transferability of workers across declining and emerging occupations. As noted by Acemoglu and Restrepo (2018), the development and expansion of new tasks and occupations are essential to outweighing the job losses caused by automation. However, the expansion of jobs into new tasks and occupations can be slowed if recent graduates and/or workers who lost their jobs due to automation do not have the required skills. We assess the proximity between two occupations based on the skills of workers employed in those occupations. Two occupations whose workers have similar skills are close, in the sense that workers can easily transfer from one to the other. In contrast, distant occupations would be those for which workers would have to learn many new skills to shift between them. Based on these measures, we assess the degree of proximity between declining and emerging occupations.

Our work on occupational and skill shifts builds upon several recent studies that look at the skills requirements of tasks and occupations (Autor, Katz, and Kearney 2006; Autor 2013; Autor and Handel 2013; Acemoglu and Autor 2012; Acemoglu and Restrepo 2018a, 2018c, 2018b). According to a recent study by McKinsey (2018), automation will increase the demand for advanced technological skills such as programming but also the demand for basic digital skills.[2] Recent studies point to the potential of AI to disrupt even non-repetitive tasks (Brynjolfsson, Rock, and Syverson 2017; Brynjolfsson and Mitchell 2017). A recent report by the Brookings Institution also highlights an increased need for technological skills in the United States (Muro et al. 2017). The share of employment in occupations that require low digital skills shrank between 2002 and 2016, while the digital components of many occupations that typically did not require digital skills, such as nurses or construction workers, have increased markedly.

McKinsey also estimates that jobs in the future will increase their requirements for social and emotional skills (for example, teaching and training others, interpersonal skills and empathy, entrepreneurship, or adaptability and continuous learning) and advanced cognitive skills, with the highest increase in creativity. Other studies, such as Deming (2017), have confirmed this growing demand for social skills in the United States. In contrast, McKinsey finds that manual and basic cognitive skills will continue to be required in the future but much less so than today.

[2] Bughin et al. (2018).

The data gleaned from this study can help direct workforce planning and learning policies.

However, despite a global debate about the future of work and the changing demand for skills, few studies have been able to capture skills-level data in a way that is dynamic, cost-effective, and reflective of the different markets, industries, and occupations that characterize different geographic localities.

This data can be particularly useful to inform workforce planning and lifelong learning policies, as the need to continually update one's skills over one's working career is rapidly increasing; digital technologies continue to influence both the emergence and decline of different occupations as well as changes in the skill sets required for many occupations.

This paper is structured as follows. It first presents a brief explanation of the value of platforms like LinkedIn for public policy and gives an overview of the key indicators and types of data used in the analysis. Second, it explores the main insights generated from an analysis of 1) emerging and declining occupations across the 10 countries examined; 2) shifts in the demand for skills; and 3) the transferability between occupations using skills similarity, as the first step to identifying the set of policies that may be needed to accelerate the reallocation of workers and economic adjustment. Finally, it concludes with a set of preliminary policy recommendations.

LARGE-SCALE DATA FROM PLATFORMS VERSUS TRADITIONAL SOURCES OF DATA

The advent of large-scale data is generating a host of non-traditional sources of workforce data with immense potential for shedding light on many labor market issues. Large-scale data platforms provide large quantities of information at a high level of granularity, at a faster speed and with lower collection costs.

The analysis in this paper relies on anonymized data from LinkedIn profiles in 10 countries: Argentina, Australia, Brazil, Chile, France, India, Mexico, South Africa, United Kingdom, and the United States.[3] These countries were chosen to ensure LinkedIn membership coverage, regional and economic development diversity. To ensure the privacy and data security of LinkedIn members, no individual-level information or personally identifiable information was ever used. The data have been aggregated by occupation, skill, and country group.

The advent of large-scale data is generating a host of non-traditional sources of workforce data with immense potential for shedding light on many labor market issues. The main advantages of using this type of data relative to more traditional sources of information are large-scale data's granularity, speed, and lower collection costs. Professional networks and job search platforms like LinkedIn's are generating enormous quantities of data at a fine level of disaggregation by geographic area, occupation, or skill level. In addition, these data are continuously updated by users, making the data particularly suitable for analyzing topics such as emerging skills needs, with the added potential of considerably reducing the cost of collecting large swaths of data on a continuous basis.

Another unique advantage of using LinkedIn data for analyzing shifting skill demands is that LinkedIn has information on the skills listed by all users. This makes it possible to discern the skills of workers hired in a given occupation, in a given period, in each country. As a result, we do not need to assume the unrealistic hypothesis that the skill requirements in a given occupation are identical across countries, as we would need to do if we utilized data available through initiatives like O*NET, as typically used in this literature, which is based on the United States' labor market (Dicarlo et al. 2016).

However, since data are only available for LinkedIn members and not for the overall population, these alternative data sources complement rather than replace traditional sources of workforce data, such as censuses, household and employer surveys, and administrative data like education, tax, social security, and unemployment records. The results and insights from this analysis need to be carefully contextualized on a country-by-country basis.

[3] Globally, LinkedIn's Economic Graph has 575 million members, 50,000 standardized skills, 26 million employers, 15 million jobs, and 60,000 educational institutions.

Three types of information was gathered from LinkedIn members: Occupations, Hires, and Skills

We utilize three types of information from LinkedIn members (for more information, see the technical appendix).

Occupations: LinkedIn members report and update their status regarding a new job or their work history. Using machine learning, LinkedIn matches their reported positions to one of its proprietary taxonomies and groups similar job titles from members' profiles based on a combination of industry, expertise, and tasks performed in those roles. The one used in this analysis contains 283 occupations.

Hires: Members report the date when they started a new position in a different company, which is used to create a measure of total hires for each year and a hiring share by occupation over a given time.

Skills: Members also showcase the set of skills they possess. For this report, we use information from 50,000 skills categorized into 249 skills clusters. See Box 1 for more information on skills in LinkedIn.

LINKEDIN'S PLATFORM CONTAINS A UNIQUE DATA SET OF 50,000 SPECIFIC MEMBER SKILLS, GATHERED FROM DIFFERENT SOURCES OF USER DATA

- **Explicit skills** come from the information that users input directly into the skills section of their profiles. The platform also automatically suggests skills that are frequently associated with the position and industry they have reported. However, these are only considered if the member confirms the suggested skill and adds it to his or her profile.
- **Implicit skills** are pulled from text inputted by users in other sections of a member's profile, such as the descriptions of tasks that accompany each role. LinkedIn uses machine learning to extract, categorize, and standardize these skills.

To analyze broad skill trends, skills are grouped together by industry expertise, functional expertise, or academic and hands-on training. A machine learning algorithm is used to group these skills into 249 larger "skill clusters." The 10,000 most frequently occurring skills were categorized into these clusters. This group of 10,000, which encompasses the vast majority of skills that people enter onto their profiles as the skills distribution on the LinkedIn platform has a very long tail. A skill cluster—such as "Development Tools", for example—may include a range of skills, such as command of Apache Storm and AppleScript and other Web development and programming tools.

Box 1. Skills on LinkedIn

Source: LinkedIn's Economic Graph

The hiring data also reflect a wide variety of industries, albeit with higher concentrations of members in certain industries across the 10 countries examined. Table 1 shows how much more important hires are in an industry in a given country, relative to the average share of members in all industries in that country. Software and IT services, for example, are relatively important in India, while retail is relatively important in 60% of the countries examined (Table 1).

Similarly, the education levels that members report in their profiles vary across countries, but most countries have a high concentration of members with at least some higher education. Most members in Latin American countries reported having a master's degree, followed by a bachelor's degree. Australia, Brazil, India, South Africa, United Kingdom, and the United States have very similar distributions of education levels, where the highest share has a bachelor's degree, followed by a master's. France has the most members with master's degrees but almost the same levels of bachelor's and associate degrees. This concentration, however, is expected in a professional network, where members tend to have a relatively high level of education.

Industry	Argentina	Australia	Brazil	Chile	France	India	Mexico	South Africa	United Kingdom	United States
Agriculture	■		■	■			■			
Arts	■				■				■	
Construction		■		■					■	
Consumer Goods	■		■	■			■			
Corporate Services			■					■	■	
Design	■			■			■			
Education		■	■	■						■
Energy & Mining				■						
Entertainment	■								■	■
Finance						■			■	■
Hardware & Networking	■			■		■	■			
Healthcare	■	■							■	■
Legal	■	■					■	■	■	
Manufacturing			■		■	■	■			
Media & Communication	■						■	■	■	
Nonprofit		■			■				■	■
Public Administration	■	■			■		■			
Public Safety			■					■	■	■
Real Estate		■			■					■
Retail		■	■		■			■	■	■
Software & IT Services						■				
Transportation & Logistics			■	■	■			■		
Wellness & Fitness	■		■							■

Table 1. Industries with high concentration of member-reported hires, by country

Source: The Economic Graph. LinkedIn. A shaded box indicates that the industry index is above 1. The index is constructed as the share of hires in each industry in each country dived by the average share of hires in all industries in each country.

RESULTS

The following sections explore some of the global insights and cross-cutting trends generated from three separate, but incremental analyses:

First, we use hiring trends to determine the rate at which occupations are incorporating workers to assess which occupations are most emerging and declining in each country, as well as across the 10 countries examined.

Second, using similar information regarding hiring trends across different occupations, we analyze the specific skills that are emerging and declining between occupations – i.e., those skills that are more, or less, in demand because of shifts in the demand for the occupations that require these skills. Because LinkedIn's data provides a unique set of data – the share of people with a specific skill in each occupation in each country – we were able to construct a new measure of change in skill demand (see technical appendix) that does not rely on assumptions of skill shifts based on occupational shifts.

And third, combining the data on both occupations and skills, we estimate the importance of a skill in an occupation by measuring how much higher is the share of LinkedIn members who possess that skill in that given occupation relative to the average share of members who possess that skill in each country.[4] Using information about the relative importance of each skill in each occupation, we estimate a matrix of pairwise correlations for every occupation present in each country to measure of how similar two occupations are based on their skill content. We then used the correlations as a distance measure between each occupation to visualize the occupations in each country as a network.

Results may indicate shifts towards skills that are more resistant to automation

EMERGING AND DECLINING OCCUPATIONS

The analysis of emerging and declining occupations[5] revealed at least three trends across the 10 countries examined: 1) consistency among the most emerging occupations across countries, led by the strong emergence of tech-intensive occupations; 2) the decline of administrative roles and technicians; and 3) the rise of "people-centric" occupations.

Many of these insights are broadly consistent with several recent studies[6] demonstrating that rapid advances in digital technologies are shifting the demand for occupations, particularly those composed of largely automatable tasks.

The changes in emerging and declining occupations identified in this section may also indicate an underlying shift toward the types of tasks and skills that may be more resistant to automation, artificial intelligence, and other rapidly advancing digital technologies. Frey and Osbourne (2017), for example, identified three "engineering bottlenecks"—three sets of tasks that have been difficult to codify and thus to automate: tasks related to perception and manipulation that are performed in unstructured, complex situations, such as operating in cramped workspaces; tasks related to creative intelligence, such as coming up with original ideas; and tasks related to social intelligence, such as understanding people's reactions in social contexts or assisting and caring for others.

Tech-intensive roles like software developers are among the top emerging occupations overall, but other emerging occupations demonstrate variation across regions.

The most rapidly emerging occupations across the 10 countries analyzed are software developers, followed by consultants, founders/owners, and business strategists. Figures 1 and 2 rank[7] the top declining and emerging occupations across the 10 countries, illustrating that many occupations are emerging consistently across all the examined countries.

[4] The index captures how over-expressed is each skill in an occupation relative to the whole economy.

[5] Emerging and declining occupations are occupations that exhibited an increasing or decreasing trend in hiring, respectively, over the sample period of 2008–2017. See the technical annex for more detail.

[6] Autor, Katz, and Kearney (2006); Autor (2013); Autor and Handel (2013); Acemoglu and Autor (2012); Acemoglu and Restrepo (2018a) (2018c).

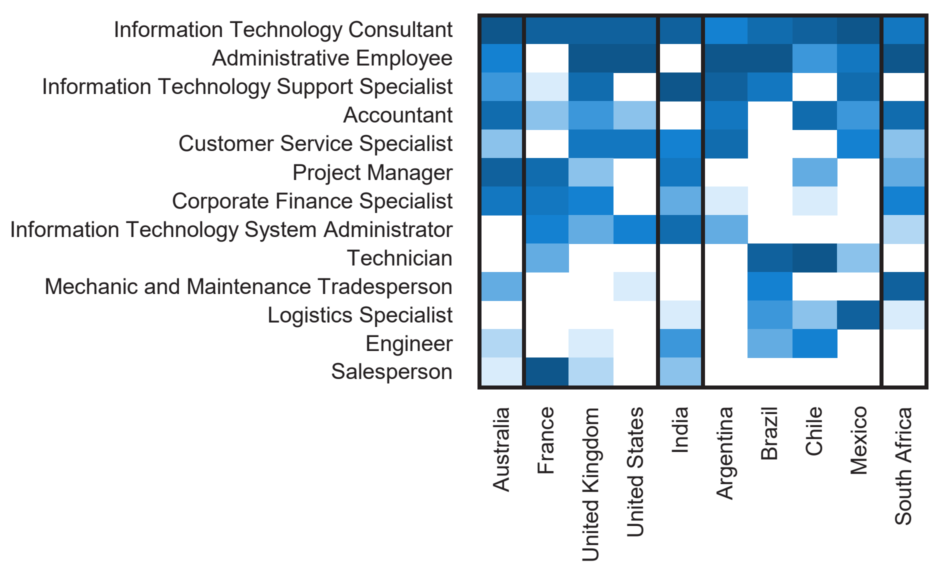
[7] Using the hiring rates for each occupation in each country, a global ranking of emerging and declining occupations was constructed using the sum of the rankings for each occupation across each country.

Software Developers are the most rapidly emerging occupation overall

The emergence of software development as the most rapidly growing occupation overall suggests that the demand for advanced tech-intensive roles is growing rapidly. Country by country, it is the top emerging occupation in six of the 10 countries; in the other four, it ranges from second to fourth most emerging. Software developers—a term that groups job titles such as Web developers, software engineers, and programmers that design, develop, and modify software systems for a range of industries and purposes—reflects the increasing digitalization of the global economy. Another emerging occupation is social media specialists, who are responsible for planning, implementing, and monitoring the social media strategies for diverse companies and organizations, which suggests that an increase in the importance of the digital economy could be driving hiring for professionals in these areas.

However, there are some discernable trends by region among other emerging occupations. The Latin American countries (Chile, Argentina, Mexico, and Brazil) as well as India, South Africa, and Australia exhibit much higher growth in founders/owners than in France, the United Kingdom, and even the United States. While the explanation for this trend merits further investigation, it may be indicative of different characteristics and trends in the local labor markets of these countries, e.g., the growth of small business or conversely a reflection of a lack of employment opportunities in largely lower-income countries (except for Australia), which results in greater entrepreneurship and self-employment, even among relatively well-educated populations represented in LinkedIn. In the US, there appears to be symptoms of a lack of dynamism among start-ups, which can explain the differences relative to Latin American countries (Casselman 2017).

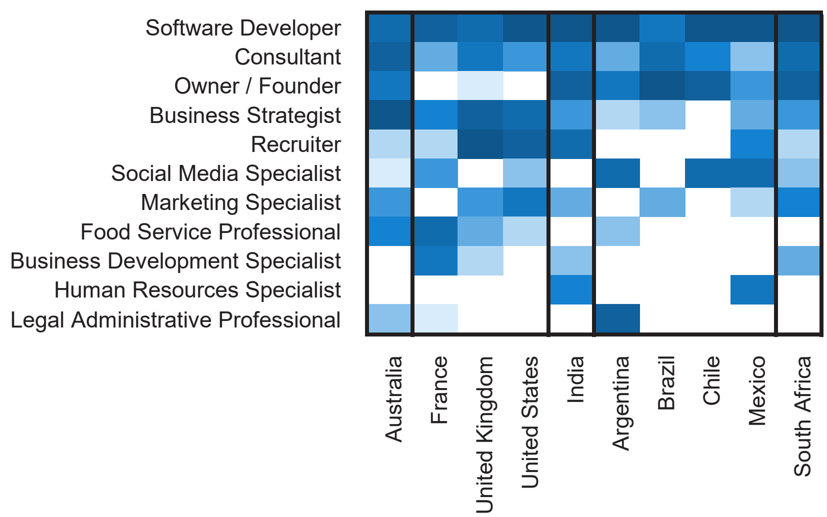
Figure 1. Most Declining Occupations Across Countries



Similarly, some occupations are emerging more strongly and consistently across the US and European countries than in Latin America. These include recruiters and marketing specialists—occupations which group job titles in LinkedIn include talent acquisition specialists and marketing managers—as well as food service professionals like bartenders, food servers, and chefs.

Figure 2, however, illustrates a pattern among emerging occupations in the examined Latin American countries: The large whitespace in Figure 2 indicates that several of the most emerging occupations in these countries are not shared with the other countries in the analysis. Some of these include lawyers, school teachers, and salespeople in Brazil; creative designers and journalists in Argentina; mental health professionals and nurses in Chile; and medical assistants in Mexico. All these occupations are among the top five most emerging in these countries (see country rankings in the annex).

Figure 2. Most Emerging Occupations Across Countries



3 out of 5 most declining occupations are technology-oriented support roles

Administrative, tech support roles, and technicians are declining.

While there is more variation across countries in terms of declining occupations, one clear trend is that not all tech-oriented jobs are growing. Of the five most declining occupations—IT consultants, administrative employees, IT support specialists, accountants, and customer service specialists—three are technology-oriented support roles. The decline in the hiring rates of IT support specialists, IT consultants, and IT system administrators may in fact be consistent with and reflect the increasing automation of these types of tech support services.

Administrative employees are the second most declining occupation in the overall ranking, which is consistent across all countries. The top jobs titles linked to this occupation on LinkedIn are administrative assistant, office manager, receptionist, executive assistant, assistant, and secretary. Software applications and other advances in technology that absorb the tasks performed by administrative employees could be driving this decline. Similarly, the decline of customer service specialists and project managers may also reflect this trend.

Technicians and other support specialists are also declining, though with important regional variations. Occupations like mechanic and maintenance tradespeople, technicians, and logistics specialists, for example, are rapidly declining among three Latin American countries—Chile, Brazil, and Mexico.

Creative and social tasks are less likely to be automated

"People-centric" occupations are emerging.

Another trend is the emergence of "people-centric" occupations, which may reflect some of the creative and social tasks highlighted as being least susceptible to automation. Social media specialists, recruiters, marketing specialists, business strategists (with job titles such as board members and chief executives), and business development specialists (with job titles such as customer adviser, client relationship manager, and business development executive) are rapidly emerging in several countries. Many of these occupations are high skill and have increasingly important digitally oriented components but also require high levels of social intelligence to gauge and elicit people's reactions and to make high-level decisions from complex information.

Service-oriented and caretaker occupations are also emerging in several countries. Some country-specific examples are the growth of schoolteachers in Brazil, medical assistants[8] in Mexico, and nurses and mental health professionals in Chile. Food service occupations like bartenders, food servers, and chefs are emerging in high-income economies such as Australia, France, the UK, the US, as well as in Argentina.

The change in the demand for workers in different occupations is likely to affect the demand for skills, as some skills are more important in certain occupations than others. As a result, changes in the employment composition will change how different skills are demanded. In the next section, we explore how changes in the demand for occupations affects the demand for skills.

EMERGING AND DECLINING SKILLS

Web design and software development are two of the fastest growing skill categories

The shift in occupations is also driving a shift in skill requirements. Several studies have attempted to measure this shift using data available from initiatives like O*NET, which rests on assumptions that skill requirements in a given occupation are identical across countries. However, data from LinkedIn provides a unique set of information on the share of people with a certain skill in each occupation for each country and the associated hiring rates of members with these skills. Using the information about the share of recent hires in each occupation that has a certain skill, we estimate how, based on these skills, changes in each occupation drive changes in the demand for skills (see technical annex for more information). Our results can be summarized as follows:

Advanced digital skill categories are among the fastest growing, with Web design and development tools as the top two emerging skills in all countries, except for Brazil.

Tech-related skills are among the fastest growing skills everywhere. In all countries except Australia and Brazil, digital skills compose at least nine of the 20 fastest growing skills (charts for each of the 10 countries can be found in the country-specific annexes). In fact, tech-related skill categories are among the top two fastest-growing skill categories in all countries except Brazil. This is not surprising, given the growth of digital technology-related occupations described in the former section. Web design and software development tools are the top two emerging skill categories almost everywhere. Other emerging skills include data storage, software development life cycle, social media management, human–computer interaction, and mobile application development (see Figure 3).

The shift in occupations also appears to be driving an increase in categories such as marketing, advertising, and graphic design. A related category that also overlaps with the tech category is digital marketing.

[8] These occupations do not appear in Figures 2 and 3 because they were not among the most common emerging occupations among the 10 countries. Country-specific rankings can be found in the country appendices.

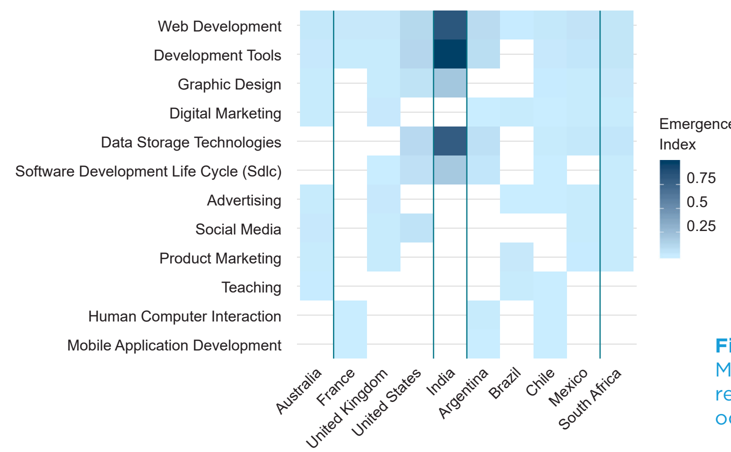


Figure 3.
Most emerging skill requirements due to occupational shifts

Interestingly, occupational shifts are also driving an increase in the demand for teaching skills, possibly because of increased skills requirements (McKinsey & Co. 2018), chief among them the digital skills gaps created by fast-changing and growing digital skill requirements.

There is a shift in demand from basic to advanced digital skills as jobs become more digitized

Administrative and management skill categories are declining, as are certain categories of tech skills.

Occupational shift also appears to be driving a decline in the demand for managerial and administrative skills (see Figure 4). The demand for project, business, people, and account management skills are in decline. So are those for leadership and negotiation skills. Given that these skills are people-centric, it is possible that while they are declining due to decline in jobs related to them, the value of such skills may be higher than before when used in combination with other technical skills. Similarly, administrative assistance and procurement skills are among the fastest declining skill categories.

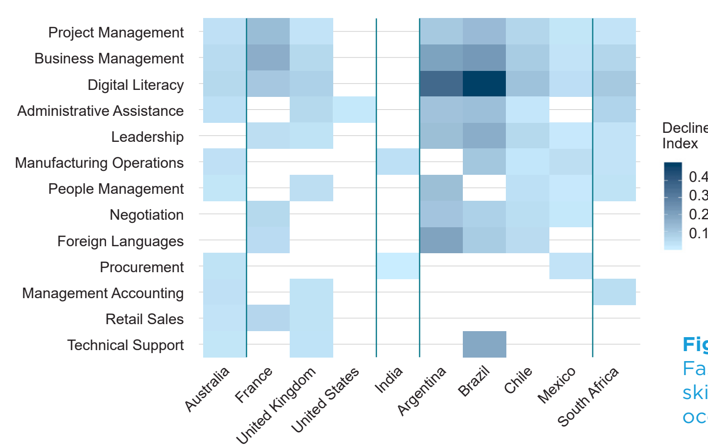


Figure 4.
Fastest declining skills as a result of occupational shifts

Some categories of tech-related skills are also declining. The data show a strong decline in the demand for digital literacy. In more than half of the countries, digital literacy—which includes a command of a range of basic digital skills and tools like Microsoft Office, Email Management, Word Processing and even Google Docs—is the skill category that shows the fastest decline. This may be driven by the fact that our analysis only accounted for changes caused by shifts in occupations. Many of the fastest growing occupations, as shown in the former section, required advanced digital skills. There may be a shift in demand from basic to advanced digital skills. Possibly, a measure of skill change that also accounted for changes in the demand for skills within each occupation would show a positive change in the demand for basic digital skills, as many occupations that up to very recently had little demand for digital skills (Bughin et al. 2018)—such as construction workers or nurses—are increasingly becoming digitized.

Identifying and understanding the most emerging and declining occupations country by country, and the associated changes in skills provides a first set of information to help inform workforce planning and policy decisions regarding training plan development, career guidance and even prioritization of resources based on emerging trends in occupations and skills. However, in the next section, we estimate how occupations are related to one another through the sets of skills shared by the workers hired into them. Potential uses of this analysis are identifying those occupations into which workers in declining occupations can transfer, identifying alternative career paths for workers wishing to switch occupations, and identifying transitions with high potential for employment growth.

A NETWORK OF OCCUPATIONS CONNECTED BY THE SKILLS THEY SHARE

Occupations are defined in the Standard Occupational Classification 2018[9] (SOC 2018) as "a collective description of a number of similar individual jobs performed, with minor variations, in different establishments" (Bureau of Labor Statistics 2018). Alternatively, we can think of occupations as being represented by the skills that their workforce possesses. In short, occupations are connected through their shared skill composition. In this section, we leverage LinkedIn's granular skills data to estimate a matrix of correlations as a measure of occupations' relatedness. This allowed us to represent all occupations as nodes in a network graph.[10]

Understanding the transferability of skills is one of the most promising areas of analysis available through LinkedIn data. Possessing transferable skills may help individuals to better withstand labor market disruptions in a dynamic digital economy.

Understanding the transferability of skills is one of the most promising areas of analysis available through LinkedIn data. Possessing transferable skills may help individuals to better withstand labor market disruptions in a dynamic digital economy, as they are applicable to many occupations. In fact, transferable skills may be key to reskilling workers in declining occupations. In addition, identifying closeness in the occupations space can help individuals to project career moves that will provide better pay or opportunities. Understanding how occupations relate to one another can help to identify potential transitions and inform labor mobility policies.

Occupations relate to one another differently in each country.

One of the first insights derived from this exercise is that each country has a different network of occupations based on the geographically-specific skill content of each occupation. Argentina and the United States stand out as the two countries with the least and most connected sets of occupations, respectively. Figure 5 shows the network graphs for these two countries. Each dot represents an occupation, which has been color-coded: The red dots are the top 10 most declining occupations. The green dots are the top 10 most emerging occupations. Orange represents declining occupations, while blue is emerging occupations. Consistent with the statistics from Table 2 in the technical annex, Argentina's network looks more disperse and disconnected than that of the United States. It is represented by several clusters of disconnected occupations around the main network. This means that occupations in the United States are more similar in terms of their shared skill content—i.e., workers in those occupations not only share similar sets of skills, but they share skills that are of

[9] SOC is a task-based classification system.

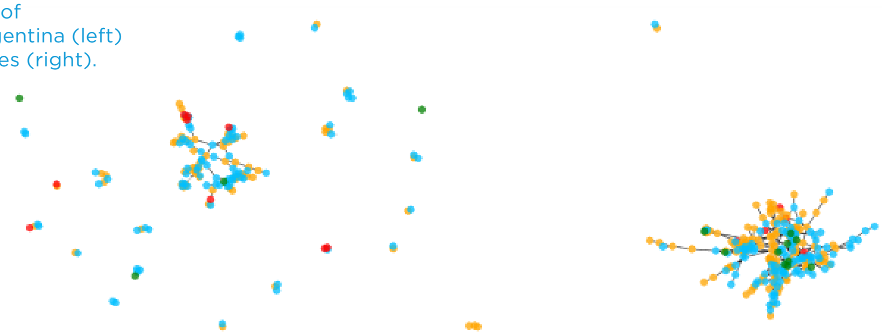
[10] Table 2 in the Technical Appendix provides some basic statistics about the networks of occupations for each country. Please refer to the appendix for a detailed exposition of the methods used.

high importance to both occupations. As occupations in Argentina are less well-connected because of less shared skill content, transitions between occupations in Argentina are may be more difficult than between occupations in the United States. This looks particularly true for some declining occupations (denoted in red) that are completely disconnected from other occupations.

The alternatives to moving out of a declining occupation vary highly across countries.

Another use of the information from the correlation matrix is to determine which occupations are possible outlets for people currently in a declining occupation. Table 2 and Table 3 show this information for Argentina and the United States. Although administrative employee is the most declining occupation in both Argentina and the United States, the former lacks any closely related occupations to which administrative employees could transfer. However, for US administrative employees, two closely related options—in terms of their shared skill content—are office workers and event planners.

Figure 5. Networks of occupations for Argentina (left) and the United States (right).



Note: Each node in the graph represents one occupation. Occupations that are closer to each other through a line have higher correlation coefficients. Occupations that are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between the disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (red), most emerging (green), declining (orange), emerging (blue).

Administrative Employee	Information Technology Support Specialist	Customer Service Specialist	Accountant	Information Technology Consultant	Military Officer	Information Technology System Administrator	Retail Salesperson	Research Analyst	Corporate Finance Specialist
		Logistics Specialist	Accounts Receivable Clerk	Technology Manager		Technology Manager	Product Manager	Project Administrator	Accountant
			Project Administrator	Information Technology System Administrator				Accountant	Business Analyst
			Accounts Payable Clerk					Finance Specialist	Accounts Receivable Clerk
			Corporate Finance Specialist					Accounts Payable Clerk	Finance Specialist
			Research Analyst					Accounts Receivable Clerk	Project Administrator
			Finance Specialist						
			Auditor						

Table 2. Closely related occupations for the 10 most declining occupations in Argentina

Note: Columns are ordered from the most to least in terms of the top 10 most declining occupations. Only occupations with a correlation coefficient of at least 0.6 are included.

Another occupation that is declining across both countries is information technology consultant. People in this occupation could transition into technology managers or information technology systems administrators, which is itself a declining occupation. However, there are more options in the US, as information technology consultant has 15 closely related alternative occupations.[11] For its part, an occupation like accountant has multiple outlets in both countries, such as accounts payable clerk, corporate finance specialist, and auditor. Occupations in the financial space appear to have several related occupations in Argentina, while those in the information technology space have a more limited number of outlets.

Administrative Employee	Information Technology Consultant	Customer Service Specialist	Information Technology System Administrator	Retail Salesperson	Military Officer	Accountant	Heavy Equipment Supervisor	Mechanic and Maintenance Tradesperson
Office Worker	Information Technology System Administrator	Staff Manager	Information Technology Consultant	Merchandiser	Program Analyst	Fund Accountant	Technician	Technician
Event Planner	Information Technology Support Specialist	Technical Support Representative	Technology Manager	Buyer Sourcing	Public Safety Professional	Auditor	Mechanic and Maintenance Tradesperson	Construction Engineer
	Database Developer		Information Security Specialist			Corporate Finance Specialist	Transportation Specialist	Heavy Equipment Supervisor
	Information Security Specialist		Information Technology Support Specialist			Personal Tax Specialist	Operations Specialist	Construction Project Planner
	Technology Manager		Network Engineer			Corporate Tax Specialist		
	Network Engineer		Database Developer			Accounts Payable Clerk		
	Chief Information Officer		Information Technology Engineer			Treasurer		
	Information Technology Engineer		Chief Technology Officer					
	Chief Technology Officer		Technical Sales Professional					
	Business Intelligence Consultant		Program Manager					
	Program Manager		Software Developer					
	Technical Sales Professional		Business Intelligence Consultant					
	Consultant		Chief Information Officer					
	Software Developer							
	Data Center Manager							

Table 3. Closely related occupations for the 10 most declining occupations in the United States

Note: Columns are ordered from the most to least in terms of the top 10 most declining occupations. Only occupations with a correlation coefficient of at least 0.6 are included.

[11] The number of alternatives for both administrative employees (AE) and information technology consultants (ITC) varies by country but appear to be related to how connected the network is. Argentina (AE: 0, ITC: 2), Australia (AE:7, ITC: 4), Brazil (AE: 1, ITC: 3), Chile (AE: 0, ICT: 3), France (AE: NA, ITC: 2), India (AE: NA, ITC: 6), Mexico (AE: 1, ITC: 2), South Africa (AE: 1, ITC: 2), United Kingdom (AE: 1, ITC: 8), United States (AE: 2, ITC: 15).

Not all transitions are possible; it may take significant upskilling to acquire the average skillset for the destination occupation.

An important consideration, however, is that not all transitions are feasible. Although two occupations may be related, it may take significant upskilling to acquire the average skillset for the destination occupation. Additionally, some transitions may have a greater overall impact in employment than others. As a result, we conducted a thought exercise using our data and results to help rank and prioritize transitions based on 1) their potential impact on overall employment; and 2) "feasibility" of the transition. The idea is to identify transitions that would provide "quick wins" for labor mobility policy.

Countries with more connected networks of occupations may have more options to help workers transition out of occupations that are declining.

To do so, we used the estimated growth rates from the emerging and declining occupations section and the correlation matrix to determine, for each country, the difference in hiring rates when switching from one occupation to its closest occupation. We then ranked all transitions in terms of their gains, regardless of occupation status of emerging or declining, to pick the top 10 transitions. To determine whether a transition is feasible, we chose an arbitrary correlation value of 0.8.[12] The results, which can be found in each country appendix, are summarized next.

The countries with the highest numbers of feasible transitions are Australia, the United Kingdom, and the United States, with six, seven, and seven transitions, respectively, from the top. In India and South Africa, only one of the top 10 transitions would be feasible, which means that the correlation to its closest occupation is less than 0.8. In Brazil and Mexico, only two of the top 10 transitions would be feasible. In Chile and France, three of the top 10 transitions would be feasible, while this number is four in Argentina.

A suggestive message from these analyses is that countries where occupations are part of a more connected network, like the United States, have more options to help workers transition out of occupations that are declining worldwide. Determining how connected countries' occupation networks are is one of the potential applications of data from professional networks like LinkedIn. For more results regarding Argentina, the United States, and the rest of countries in our sample of the G20, please refer to the country-specific annexes at the end of this document and to the Technical Appendix, where we describe in detail the methods and data used for this analysis.

The insights derived in this section may have important implications for policy. Knowing that people working in a declining occupation have a set of skills that are also found among workers in emerging occupations will allow governments and other stakeholders to adjust their interventions. Training, intermediation, and other workforce planning and programs can be adjusted to help individuals with transferable skills to more easily transition from declining into emerging occupations, while at the same time complementing those skills with new industry- or occupation-specific skills. Current and potential workers in emerging occupations can benefit as well by identifying alternative career transitions, which expands the options available for a worker's horizontal and vertical mobility.

[12] During the exercise used different values starting from 0.6, and the results were similar. However, different thresholds could be established yielding a different set of options, depending on the criteria established for the threshold.

POLICY IMPLICATIONS & RECOMMENDATIONS

There's value in making new sources of data interoperable, shared, and complementary to traditional sources of information

As technology continues to accelerate the pace of change in the workplace, obtaining better and more timely insights on the changing demand for skills and occupations has become a pressing challenge for all countries. From the analysis performed based on this strategic partnership between the IDB and LinkedIn, we derive four key conclusions:

New sources of large-scale data provide timely and granular labor market information that is highly relevant for policy. The analysis performed in this study highlights the richness of the information available in some of these new data sources. While other sources of traditional data can provide information on emerging and declining occupations, very few data sources can provide timely and cost-effective data on shifting skill requirements or skill transferability. While further data are needed to validate and further contextualize the trends described here, these unique insights on transferability and shifting skill requirements can be used to adjust and steer education and labor policy in a rapidly shifting environment.

Across all examined countries, tech-related occupations and tech- related skills are on the rise. Occupations like software developer and skills like Web development and development tools are on the rise. Education and training providers must adjust their curriculums and supply of courses to ensure that learners are acquiring a command of the specific tools that are most in demand and generate professionals who can meet this growing demand. This may imply shifting some of resources from administration/ management courses, toward courses that teach advanced digital skills. Categories such as marketing, advertising, and graphic design are also on the rise, as so far, people with these skills perform tasks that are difficult to automate. Design and marketing combined with digital skills are also categories on the rise.

People-centric roles are also growing. Many of these occupations are high skill and have increasingly important digitally oriented components but also require high levels of social intelligence to gauge and elicit people's reactions and to make high-level decisions from complex information. Service-oriented and caretaker occupations are also emerging in several countries. All of these appear to be the least likely occupations to be automated.

Countries with more connected networks of occupations will have a better chance of helping workers to transition out of declining occupations. Our results showed that in countries where occupations are closely related, workers in declining occupations have a wider array of options. These results also hold when analyzing the occupational transitions that yield the highest gains in hiring rates. Identifying how connected occupations are requires access to granular data for skills and occupations to construct measures of occupational relatedness. Fortunately, these data are becoming readily available to policymakers.

However, the analysis presented here needs to be interpreted with care. Occupations and skills are self-reported by members. Not all skills reported by members may be required or needed by employers. Similarly, members may report the skills they think employers look for and underreport skills that they consider less important. This may be the reason why soft skills appear less important in this study than in other recent studies. Another word of caution is that we have only measured changes in skill demand documented due to occupational shifts. A more complete measure, capturing changes in skill requirements within each occupation could provide distinct measures of changing skill needs.

As a final reflection, these results also show the desirability and usefulness of investing in the infrastructure to make new sources of data interoperable, shared across government agencies, and complementary to traditional sources of information. Modern labor market information systems that emphasize integration and interoperability are necessary to facilitate the sharing and dissemination of different sources and types of data to generate a more complete and timely picture of the labor market. This intelligence can be shared with a range of stakeholders, including parents and students, workers, employers, policymakers, and education and training providers.

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COUNTRY APPENDICES

ARGENTINA

Argentina: Emerging Occupations	Rank
Software Developer	1
Legal Administrative Professional	2
Social Media Specialist	3
Owner / Founder	4
Creative Designer	5
Journalist	6
Consultant	7
Food Service Professional	8
Business Strategist	9
Architect	10

Argentina: Declining Occupations	Rank
Administrative Employee	1
Information Technology Support Specialist	2
Customer Service Specialist	3
Accountant	4
Information Technology Consultant	5
Military Officer	6
Information Technology System Administrator	7
Retail Salesperson	8
Research Analyst	9
Corporate Finance Specialist	10

Note: These tables rank the top 10 most emerging and declining occupations in Argentina according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Administrative Employee	Salesperson	1	0.42
Contract Administrator	Legal Administrative Professional	2	0.25
Compliance Specialist	Legal Administrative Professional	3	0.45
Information Technology Support Specialist	Database Developer	4	0.52
Customer Service Specialist	Logistics Specialist	5	0.95
Photographer	Social Media Specialist	6	0.20
Information Technology Consultant	Technology Manager	7	0.81
Accountant	Accounts Receivable Clerk	8	0.82
Information Technology System Administrator	Technology Manager	9	0.93
Retail Salesperson	Product Manager	10	0.67

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

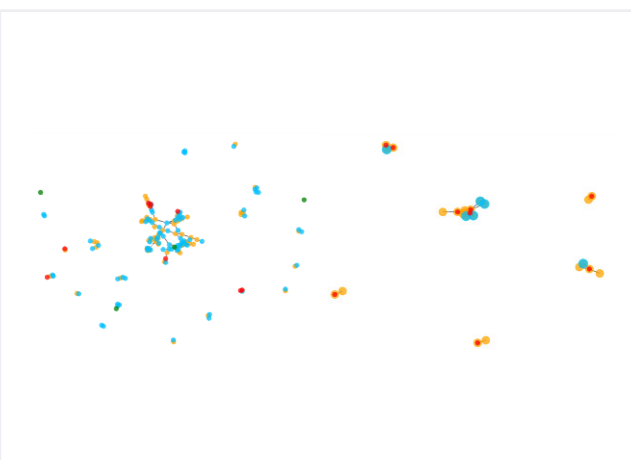

Figure A. Network of all occupations (left) and most declining occupations (right).

Note: Each node in the graph represents one occupation. Occupations which are closer to each other through a line have higher correlations coefficients. Occupations which are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (Red), most emerging (Green, only in all occupations graph), declining (orange), emerging (blue).

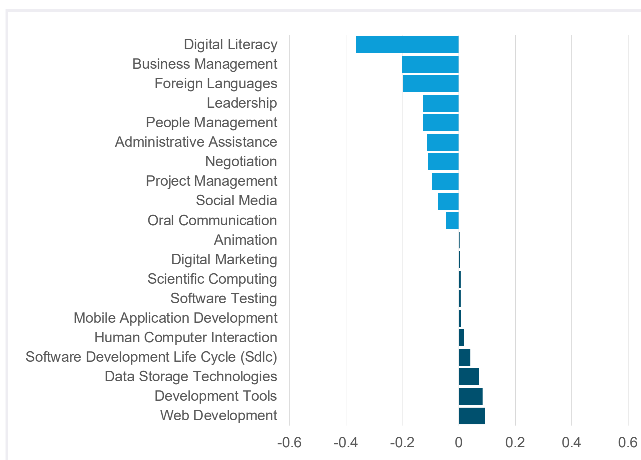

Figure B. Top Emerging and declining skills due to Occupational Shifts

AUSTRALIA

Australia: Emerging Occupations	Rank
Business Strategist	1
Consultant	2
Software Developer	3
Owner / Founder	4
Food Service Professional	5
Marketing Specialist	6
School Teacher	7
Legal Administrative Professional	8
Recruiter	9
Social Media Specialist	10

Australia: Declining Occupations	Rank
Information Technology Consultant	1
Project Manager	2
Accountant	3
Corporate Finance Specialist	4
Administrative Employee	5
Information Technology Support Specialist	6
Mechanic and Maintenance Tradesperson	7
Customer Service Specialist	8
Engineer	9
Salesperson	10

Note: These tables rank the top 10 most emerging and declining occupationsn Australia according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Project Manager	Consultant	1	0.90
Student	Consultant	2	0.71
Executive Director	Consultant	3	0.84
Technical Sales Professional	Telecommunications Specialist	4	0.65
Partner	Lawyer	5	0.83
Social Media Specialist	Website Manager	6	0.86
Administrative Employee	Consultant	7	0.75
Investment Trader	Treasurer	8	0.53
Lawyer	Legal Administrative Professional	9	0.93
Corporate Tax Specialist	Personal Tax Specialist	10	0.99

Transitions with the highest expected hiring rate gains

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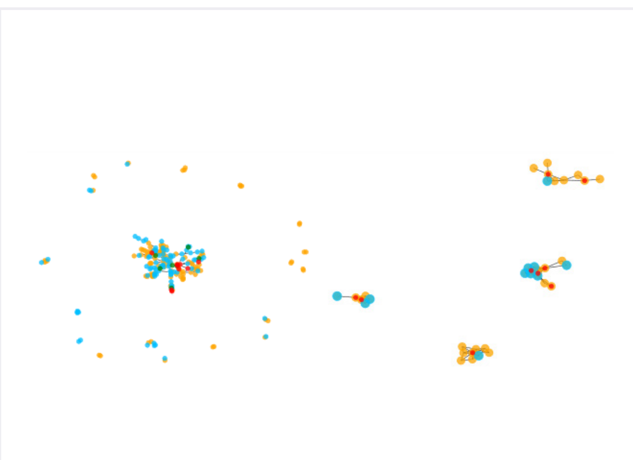

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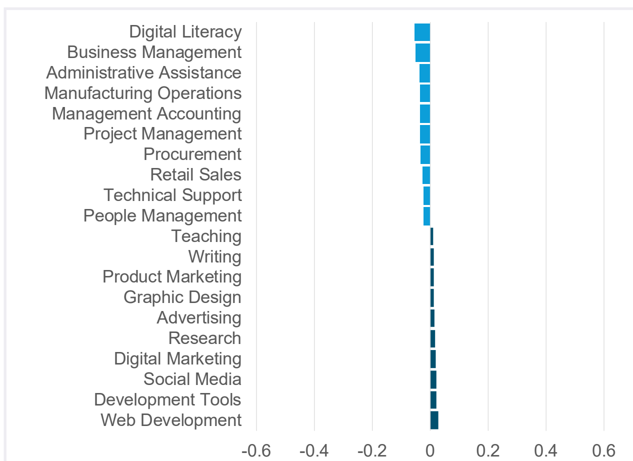

Figure B. Top Emerging and declining skills due to Occupational Shifts

BRAZIL

Brazil: Emerging Occupations	Rank
Owner / Founder	1
Lawyer	2
Consultant	3
Software Developer	4
School Teacher	5
Salesperson	6
Marketing Specialist	7
Business Strategist	8
Mental Health Professional	9
Website Manager	10

Brazil: Declining Occupations	Rank
Business Analyst	1
Military Officer	2
Computer Aided Designer	3
Engineer	4
Logistics Specialist	5
Mechanic and Maintenance Tradesperson	6
Information Technology Support Specialist	7
Information Technology Consultant	8
Technician	9
Administrative Employee	10

Note: These tables rank the top 10 most emerging and declining occupations in Brazil according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Lawyer	Partner	1	0.82
Database Developer	Chief Technology Officer	2	0.91
Agriculturist	Technical Sales Professional	3	0.80
Control Systems Engineer	Electrical Engineer	4	0.32
Executive Director	Consultant	5	0.65
Project Manager	Consultant	6	0.80
Student	Software Developer	7	0.57
Information Technology Consultant	Software Developer	8	0.77
Legal Administrative Professional	Lawyer	9	0.73
Military Officer	Public Safety Professional	10	0.61

Transitions with the highest expected hiring rate gains

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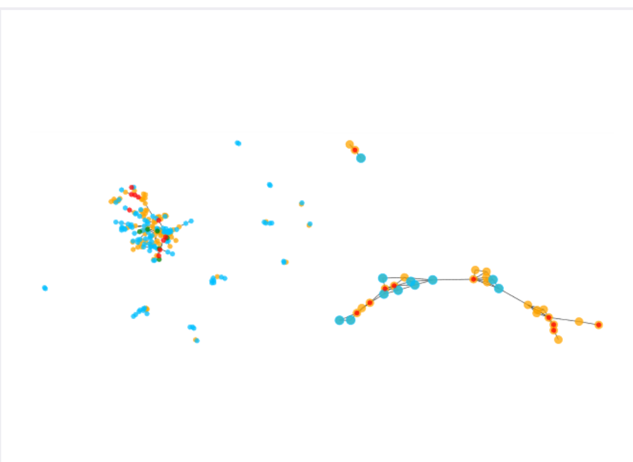

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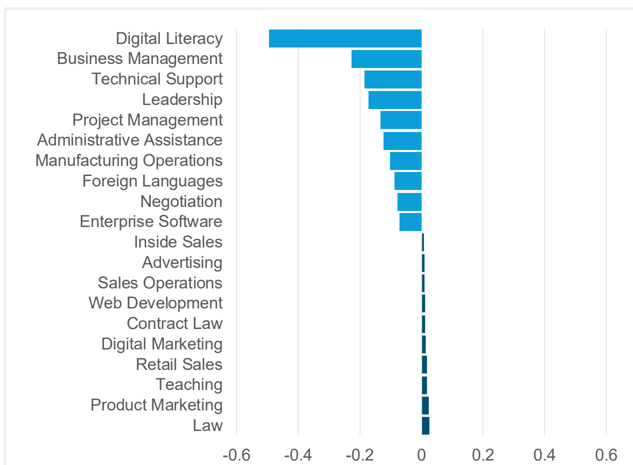


Figure B. Top Emerging and declining skills due to Occupational Shifts

CHILE

Chile: Emerging Occupations	Rank
Software Developer	1
Owner / Founder	2
Social Media Specialist	3
Mental Health Professional	4
Consultant	5
Nurse	6
Dietitian	7
Physical Therapist	8
Creative Designer	9
Commercial Real Estate Specialist	10

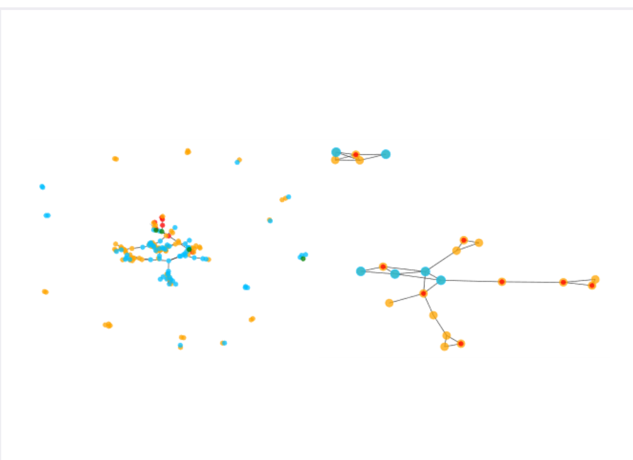
Chile: Declining Occupations	Rank
Technician	1
Information Technology Consultant	2
Accountant	3
Product Manager	4
Engineer	5
Administrative Employee	6
Project Manager	7
Logistics Specialist	8
Business Analyst	9
Corporate Finance Specialist	10

Note: These tables rank the top 10 most emerging and declining occupations in Chile according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Project Manager	Consultant	1	0.64
Business Analyst	Consultant	2	0.58
Information Technology Consultant	Technology Manager	3	0.75
Product Manager	Marketing Specialist	4	0.58
Technician	Mechanic & Maintenance Tradesperson	5	0.89
Author	Social Media Specialist	6	0.71
Accountant	Auditor	7	0.87
Food Service Professional	Dietitian	8	0.19
Website Manager	Social Media Specialist	9	0.87
Public Relations Specialist	Social Media Specialist	10	0.80

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.



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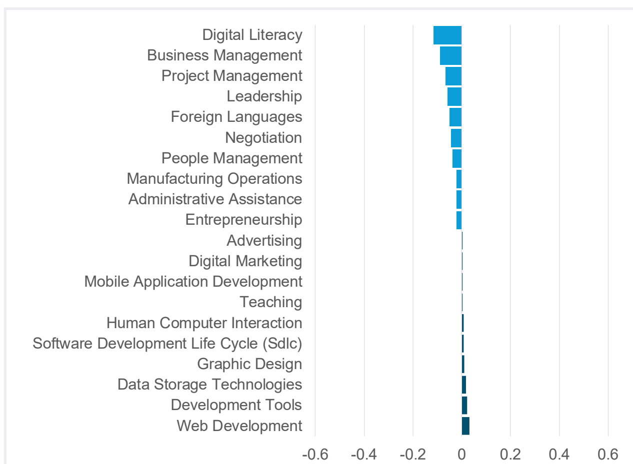

Figure B. Top Emerging and declining skills due to Occupational Shifts

FRANCE

France: Emerging Occupations	Rank
Performer	1
Software Developer	2
Food Service Professional	3
Business Development Specialist	4
Business Strategist	5
Social Media Specialist	6
Consultant	7
Production Crew	8
Recruiter	9
Legal Administrative Professional	10

France: Declining Occupations	Rank
Salesperson	1
Information Technology Consultant	2
Project Manager	3
Corporate Finance Specialist	4
Information Technology System Administrator	5
Research Fellow	6
Technician	7
Accountant	8
Product Manager	9
Information Technology Support Specialist	10

Note: These tables rank the top 10 most emerging and declining occupations in France according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Salesperson	Business Development Specialist	1	0.13
Export Sales Specialist	Food Service Professional	2	0.56
Information Technology Consultant	Technology Manager	3	0.92
Data Analyst	Software Developer	4	0.61
Author	Social Media Specialist	5	0.66
Corporate Finance Specialist	Administrative Employee	6	0.53
Human Resources Specialist	Recruiter	7	0.85
Research Fellow	Laboratory Scientist	8	0.75
Product Manager	Marketing Communications Special	9	0.68
Wealth Manager	Legal Administrative Professional	10	0.83

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

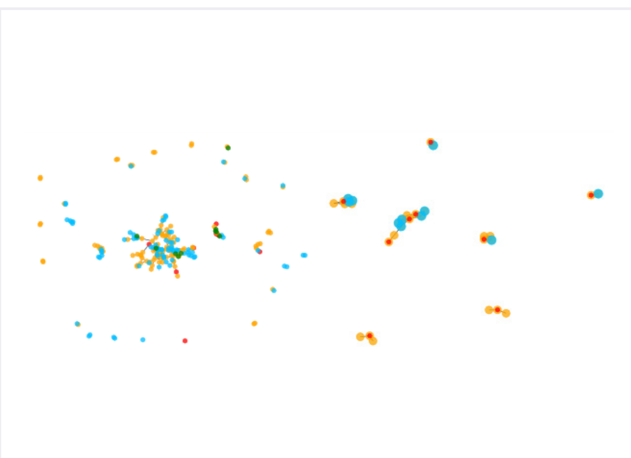

Figure A. Network of all occupations (left) and most declining occupations (right).

Note: Each node in the graph represents one occupation. Occupations which are closer to each other through a line have higher correlations coefficients. Occupations which are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (Red), most emerging (Green, only in all occupations graph), declining (orange), emerging (blue).

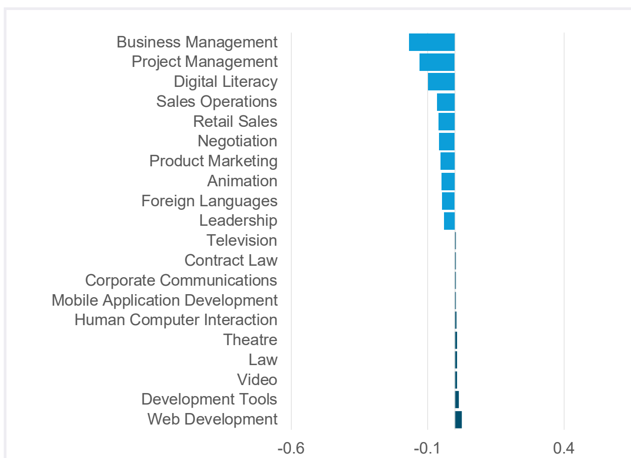

Figure B. Top Emerging and declining skills due to Occupational Shifts

INDIA

India: Emerging Occupations	Rank
Software Developer	1
Owner / Founder	2
Recruiter	3
Consultant	4
Human Resources Specialist	5
Business Strategist	6
Marketing Specialist	7
Business Development Specialist	8
Online Marketing Manager	9
Author	10

India: Declining Occupations	Rank
Information Technology Support Specialist	1
Information Technology Consultant	2
Information Technology System Administrator	3
Project Manager	4
Customer Service Specialist	5
Engineer	6
Corporate Finance Specialist	7
Salesperson	8
Database Developer	9
Logistics Specialist	10

Note: These tables rank the top 10 most emerging and declining occupations in India according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Chief Technology Officer	Software Developer	1	0.76
Project Manager	Business Strategist	2	0.75
Physician	Consultant	3	0.40
Business Analyst	Recruiter	4	0.83
Customer Service Specialist	Branch Bank Employee	5	0.77
Operations Specialist	Business Development Specialist	6	0.80
Engineer	Construction Engineer	7	0.78
Banking Sales Consultant	Business Development Specialist	8	0.56
Language and Localization Specia	Author	9	0.63
Publisher	Advertising Specialist	10	0.70

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

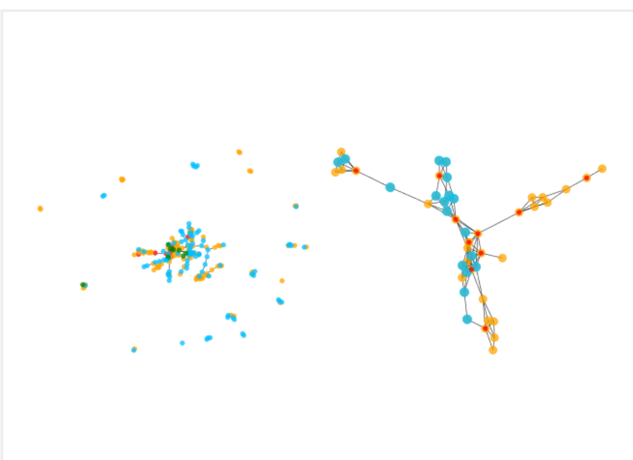

Figure A. Network of all occupations (left) and most declining occupations (right).

Note: Each node in the graph represents one occupation. Occupations which are closer to each other through a line have higher correlations coefficients. Occupations which are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (Red), most emerging (Green, only in all occupations graph), declining (orange), emerging (blue).

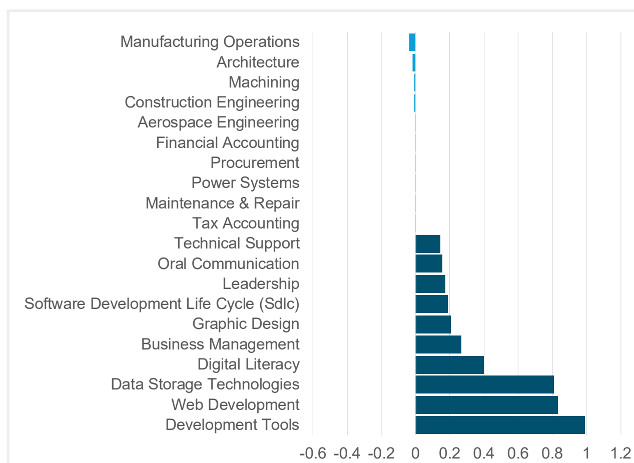

Figure B. Top Emerging and declining skills due to Occupational Shifts

MEXICO

Mexico: Emerging Occupations	Rank
Software Developer	1
Medical Assistant	2
Social Media Specialist	3
Human Resources Specialist	4
Recruiter	5
Owner / Founder	6
Business Strategist	7
Consultant	8
Marketing Specialist	9
Advertising Specialist	10

Mexico: Declining Occupations	Rank
Information Technology Consultant	1
Logistics Specialist	2
Information Technology Support Specialist	3
Administrative Employee	4
Customer Service Specialist	5
Accountant	6
Manufacturing Operations Manager	7
Technician	8
School Teacher	9
Project Administrator	10

Note: These tables rank the top 10 most emerging and declining occupations in Mexico according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Nurse	Medical Assistant	1	0.38
Information Technology Support Specialist	Business Analyst	2	0.65
Logistics Specialist	Transportation Specialist	3	0.77
Physician	Medical Assistant	4	0.17
Corporate Finance Specialist	Business Strategist	5	0.87
Customer Service Specialist	Project Manager	6	0.77
Information Technology Consultant	Customer Service Specialist	7	0.76
Accountant	Accounts Receivable Clerk	8	0.84
School Teacher	Education Administrator	9	0.57
Construction Engineer	Civil Engineer	10	0.55

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

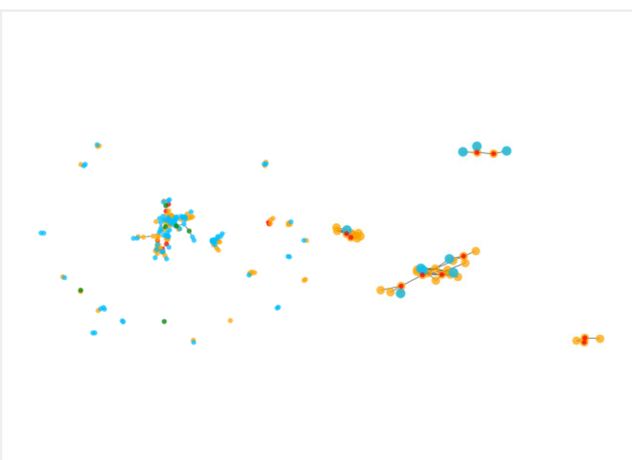

Figure A. Network of all occupations (left) and most declining occupations (right).

Note: Each node in the graph represents one occupation. Occupations which are closer to each other through a line have higher correlations coefficients. Occupations which are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (Red), most emerging (Green, only in all occupations graph), declining (orange), emerging (blue).

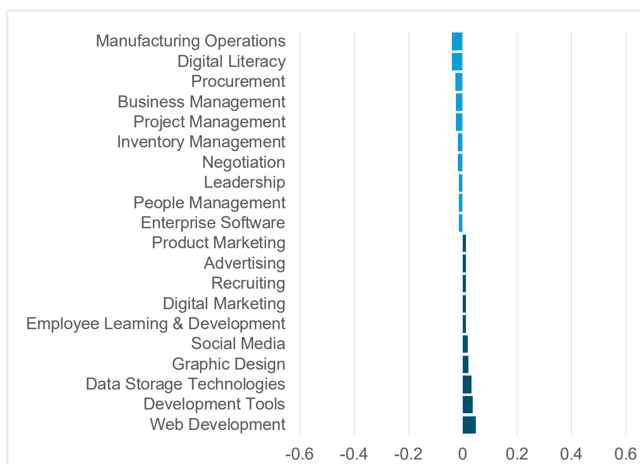

Figure B. Top Emerging and declining skills due to Occupational Shifts

SOUTH AFRICA

South Africa: Emerging Occupations	Rank
Software Developer	1
Owner / Founder	2
Consultant	3
Research Fellow	4
Marketing Specialist	5
Business Strategist	6
Business Development Specialist	7
Social Media Specialist	8
Recruiter	9
Contract Worker	10

South Africa: Declining Occupations	Rank
Administrative Employee	1
Mechanic and Maintenance Tradesperson	2
Accountant	3
Information Technology Consultant	4
Corporate Finance Specialist	5
Auditor	6
Project Manager	7
Customer Service Specialist	8
Information Technology System Administrator	9
Logistics Specialist	10

Note: These tables rank the top 10 most emerging and declining occupations in South Africa according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Technology Manager	Software Developer	1	0.73
Administrative Employee	Operations Specialist	2	0.67
Accountant	Accounts Payable Clerk	3	0.65
Corporate Finance Specialist	Partner	4	0.67
Auditor	Personal Tax Specialist	5	0.76
Human Resources Specialist	Recruiter	6	0.65
Customer Service Specialist	Operations Specialist	7	0.70
Heavy Equipment Supervisor	Contract worker	8	0.69
Information Technology Consultan	Information Technology Support S	9	0.91
Quality Assurance Tester	Contract worker	10	0.52

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

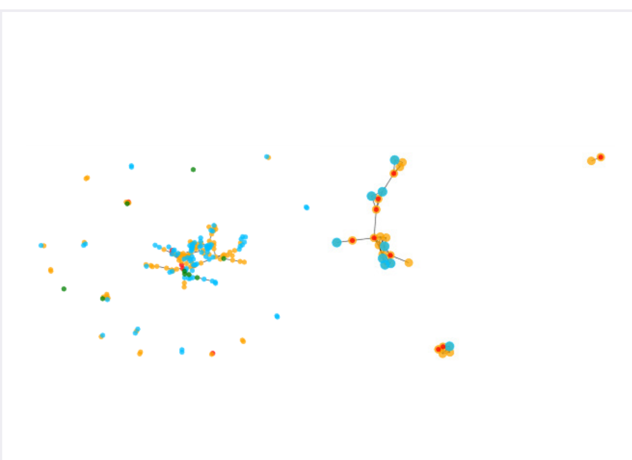

Figure A. Network of all occupations (left) and most declining occupations (right).

Note: Each node in the graph represents one occupation. Occupations which are closer to each other through a line have higher correlations coefficients. Occupations which are disconnected from each other have either a zero or not statistically significant correlation coefficient between them. The actual distance between disconnected nodes does not necessarily reflect the distance between occupations. Color code: Most declining (Red), most emerging (Green, only in all occupations graph), declining (orange), emerging (blue).

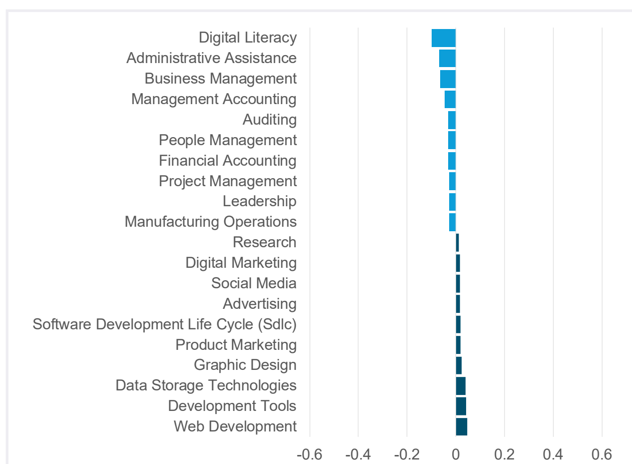

Figure B. Top Emerging and declining skills due to Occupational Shifts

UNITED KINGDOM

United Kingdom: Emerging Occupations	Rank
Recruiter	1
Business Strategist	2
Software Developer	3
Consultant	4
Production Crew	5
Marketing Specialist	6
Food Service Professional	7
Production Editor	8
Business Development Specialist	9
Owner / Founder	10

United Kingdom: Declining Occupations	Rank
Administrative Employee	1
Information Technology Consultant	2
Information Technology Support Specialist	3
Customer Service Specialist	4
Corporate Finance Specialist	5
Accountant	6
Information Technology System Administrator	7
Project Manager	8
Salesperson	9
Engineer	10

Note: These tables rank the top 10 most emerging and declining occupations in the United Kingdom according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Human Resources Specialist	Recruiter	1	0.61
Administrative Employee	Retail Salesperson	2	0.62
Customer Service Specialist	Telecommunications Specialist	3	0.80
Chief Technology Officer	Software Developer	4	0.89
Accountant	Accounts Payable Clerk	5	0.82
Entertainment Administrator	Production Crew	6	0.82
Corporate Finance Specialist	Business Analyst	7	0.76
Information Technology Consultant	Information Technology System Ad	8	0.90
Business Development Specialist	Business Strategist	9	0.81
Finance Specialist	Treasurer	10	0.94

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.

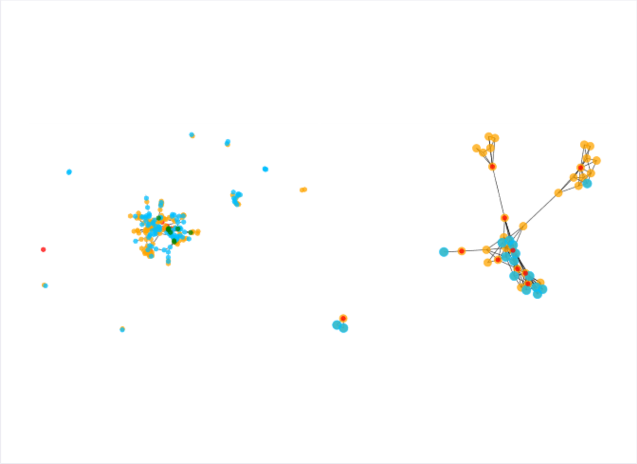

Figure A. Network of all occupations (left) and most declining occupations (right).

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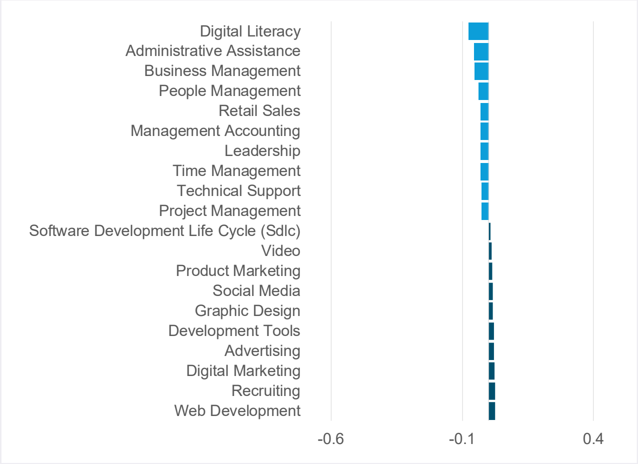


Figure B. Top Emerging and declining skills due to Occupational Shifts

UNITED STATES

United States: Emerging Occupations	Rank
Software Developer	1
Recruiter	2
Business Strategist	3
Marketing Specialist	4
Real Estate Broker	5
Consultant	6
Research Fellow	7
Social Media Specialist	8
Food Service Professional	9
Data Analyst	10

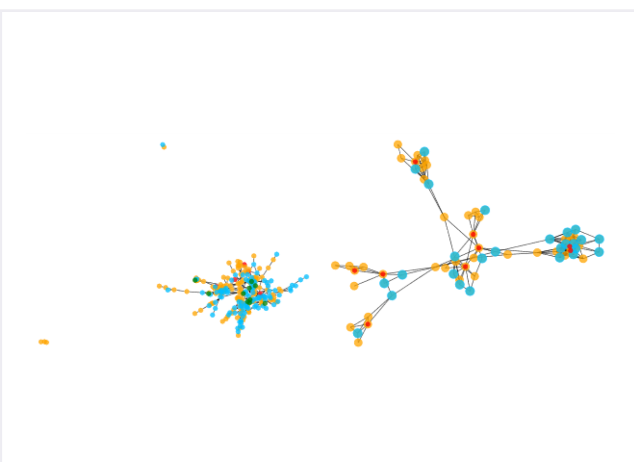
United States: Declining Occupations	Rank
Administrative Employee	1
Information Technology Consultant	2
Owner / Founder	3
Customer Service Specialist	4
Information Technology System Administrator	5
Retail Salesperson	6
Military Officer	7
Accountant	8
Heavy Equipment Supervisor	9
Mechanic and Maintenance Tradesperson	10

Note: These tables rank the top 10 most emerging and declining occupations in the United States according to the analysis of hiring rates for each occupation between 2007-2018 using LinkedIn's data for that country.

From	To	Ranking	Correlation
Chief Technology Officer	Software Developer	1	0.88
Information Technology Engineer	Software Developer	2	0.86
Administrative Employee	Office Worker	3	0.76
Customer Service Specialist	Staff Manager	4	0.65
Property Manager	Real Estate Broker	5	0.86
Corporate Board Member	Business Strategist	6	0.81
New Home Salesperson	Real Estate Broker	7	0.94
Information Technology Consultant	Information Technology System Admin	8	0.88
Food Technologist	Food Service Professional	9	0.46
Advertising Specialist	Marketing Specialist	10	0.94

Transitions with the highest expected hiring rate gains

Note: This table ranks the top 10 transitions to the closest occupation that would generate the highest gains in hiring rates. Last column shows the correlation between both occupations. Higher correlations make the transition more likely.



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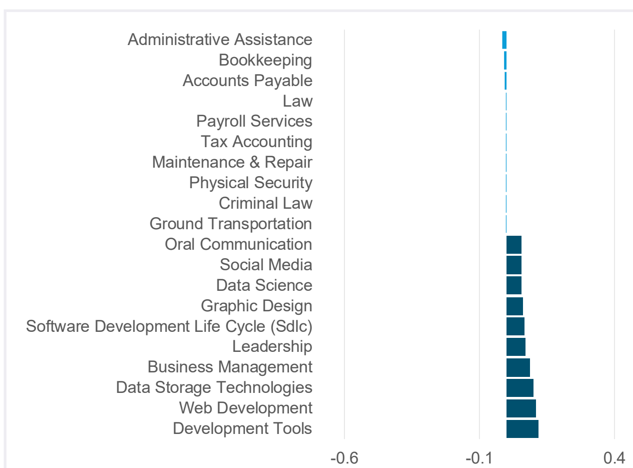


Figure B. Top Emerging and declining skills due to Occupational Shifts

TECHNICAL APPENDIX

Table 1. Definitions and Concepts used in the report

Concept	Definition
Occupation	Members include their job history (positions and roles) as unstructured text. Then, machine learning algorithms categorize these into occupations. LinkedIn has different occupation taxonomies with different levels of granularity. This analysis used a taxonomy of 283 occupations.
Skill	There are three ways to capture skills from LinkedIn member profiles: implicit, inferred, and explicit. Explicit are the skills members confirm or write into their profile. Implicit skills are ones that are extracted from other text in member profiles, but not entered in the skills section (e.g. someone writes "I use Microsoft Office to write legal documents" in the description box for their role). Inferred skills are ones that are inferred based on information in their profile but are not included in the other 2 categories. The analysis in this paper considered implicit and explicit skills. It did not use inferred skills. It also did not consider "endorsements" of skills by other members.
Skill Cluster	LinkedIn has a set of 249 skill clusters. To develop these clusters, team of taxonomists generated a set of cluster names to ensure representation across all industries, functions, and academic/vocational training based on common taxonomies such as ISIC, NAICS O*NET, CIP code and ICBF. An NLP model that uses embedding techniques was run to assign which cluster is 'closest' to each skill. The distance is defined using an embedding space that is developed using co-occurrence of skills. For example, 'C++', 'Java', 'Python', may often appear together on the profiles of software developers and thus they have a close distance to each other. Using the distance measure, 'C++', 'Java', 'Python' could be grouped into the cluster of 'Development Tools'.
Hiring	We looked at member profiles and for each position took the start date as the year of "hire". If a member changes positions but remains with the same employer, this data is not counted as a hire.

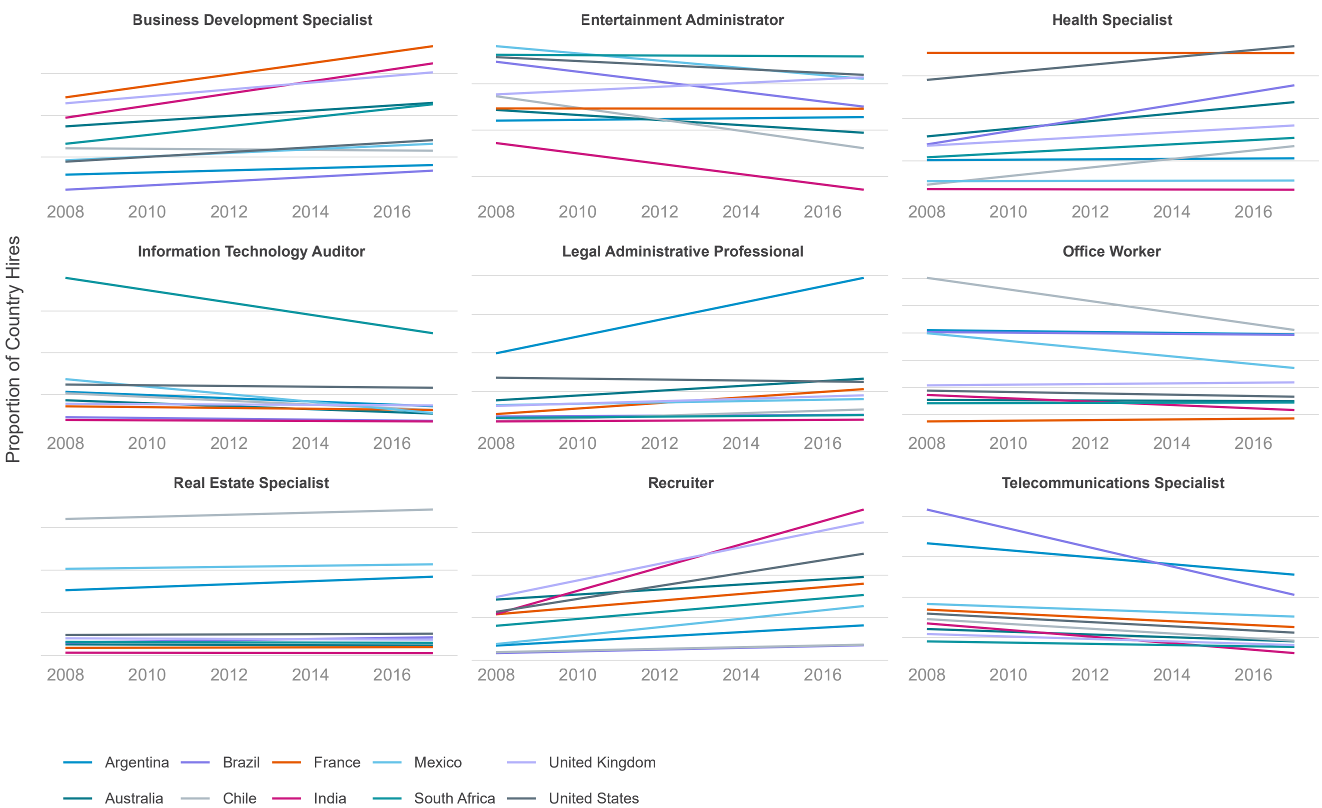
METHODS USED IN THE ANALYSIS

Calculating emerging and declining occupations

For each country and year, hiring for each occupation is measured as a proportion of total hiring for each country-year. We estimated a hiring time trend for each occupation-country combination in the period 2008-2017. We used a linear model to regress the hiring rate on a year variable to identify the linear trend of hiring to smooth yearly variation. We then ranked all occupations according to their hiring trends to pick the top ten emerging and declining occupations according to this metric.

Occupations that are emerging and declining are defined as those with the greatest increase or decrease (respectively) in hiring proportions over the observed period. Thus, the identification of emerging and declining occupations is based on the slope of each regression line. Figure 14 shows some examples of smoothing by linear regression for the same occupation in each of the ten countries included in our analysis. At first sight, most occupations show similar trends across countries. This is the case of Business Development Specialist in our example. Recruiter, which was identified as an emerging occupation, certainly shows a steep line for countries like India and the United Kingdom, and an increasing, but slower, trend in the rest. This implies that between 2008 and 2017 the Recruiter hiring rate varied across these ten countries.

Figure 1. Hiring Trends for Selected Occupations Compared by Country



Calculating changes in skill demand

One of the key features of LinkedIn data is that they allow us to estimate confidently the share of workers with a specific skill in an occupation at a precise point in time for each country. These skills are those reported by workers who are currently employed in each occupation. A key contribution of this paper is proposing a decomposition which allows us to measure the changes in the demand for skills. While data limitations only allowed us to capture the component that is due to changes in occupational hiring, we believe that applying this formula to other sources of data could provide valuable insights to policy makers. We now describe how we derive this formula and its main insights.

We define the number of workers in occupation i with skill k at time t by N_{ikt}. Let N_{it} and N_{ikt} denote the total number of workers in occupation i and the total number of workers who have skill k. By following a sequence of arithmetic operations, we can derive a formula that captures the change in the hiring rate of workers who have skill k between two periods. This formula expresses the change as the sum of two components: 1-The between component, which captures how the demand for skills changes because the demand for workers in each occupation changes and 2- The within component, which captures how the demand for skill changes because the share of workers with a certain skill changes for each occupation.

$$N_{ikt} \equiv N_{ikt} \quad (1)$$

$$N_{ikt} \equiv \frac{N_{ikt}}{N_{it}} * N_{it} \quad (2)$$

$$\sum_i N_{ikt} \equiv \sum_i \frac{N_{ikt}}{N_{it}} * N_{it} \quad (3)$$

$$\sum_i N_{ikt} = \sum_i S_{ikt} * N_{it} \quad (4)$$

$$where\ S_{ikt} = \frac{N_{ikt}}{N_{it}}$$

$$N_{kt} = \sum_i S_{ikt} * N_{it} \quad (5)$$

$$H_{kt_1} = \sum_i S_{ikt_1} * H_{it_1} \quad (6)$$

$$where\ H_{kt_1} = \frac{\Delta N_{kt}}{\Delta N_t}\ and\ H_{kt_1} = \frac{\Delta N_{it}}{\Delta N_t}$$

$$\Delta H_{k\tau} = \sum_i S_{ikt_1} * \Delta H_{i\tau} + \sum_i \Delta S_{ik\tau} * H_{it_1} \quad (7)$$

Step (1) is an identity. In step (2) we multiply and divide by the number of workers in occupation i. In step (3) we add across all occupations on both sides of the equation. In step (4) use the definition for the share of workers in occupation i who have skill k. In step (5) we use the fact that adding across occupations, provides the total number of workers with skill k.

In step (6) we fix the moment at which the share of workers in occupation i with skill k is measured and express equation (5) as the hiring rate within that period. The hiring rate is defined as the change in employment in an occupation (or a given skill) as a fraction of the total change in employments within that period. Finally, in step (7) we express the change in the hiring rates as the total (discrete) differential. The changes are computed between the periods τ and t_1. The first part is the between component and the second is the within component.

The between component provides a measure of the changes in skill demand associated with occupation shifts, assuming that the skill content of each occupation has not changed. The within component is the change in skills driven by the changes in skills within each occupation. Due to data limitations, we cannot measure changes in skill utilization within occupations during the period of study. Therefore, all our measures of skill change refer uniquely to those resulting of occupational shifts.

Constructing the occupation-skills network graphs

We estimate the importance of a skill in an occupation by measuring how much higher is the share of LinkedIn members who possess that skill in that given occupation relative to the average share of members who possess that skill in each country.[16] Based on these measures, we characterize each occupation by a set of skill importance indexes and estimate proximity between occupations by calculating the correlation coefficients for every pair of occupations in each country. We only kept the correlation coefficients which were statistically significant. The result is a matrix relating every occupation to every other in each of the 10 countries in our sample. We then treated correlations as distance measures to be represented in a network graph. Higher values of correlations represent shorter distances while lower correlations values represent longer ones. The nodes in each graph are the occupations, while the edges represent the correlation between occupations. For visualization purposes we kept correlations that had a value of at least 0.5 and used a drawing method called spring layout which positions nodes using a Fruchterman-Reingold force-directed algorithm.[17]

In Table 2, The United States has, on average, 3.7 related occupations for every occupation while Argentina has 1.6, indicating that the degree of similarity between occupations appears to be higher in the former.

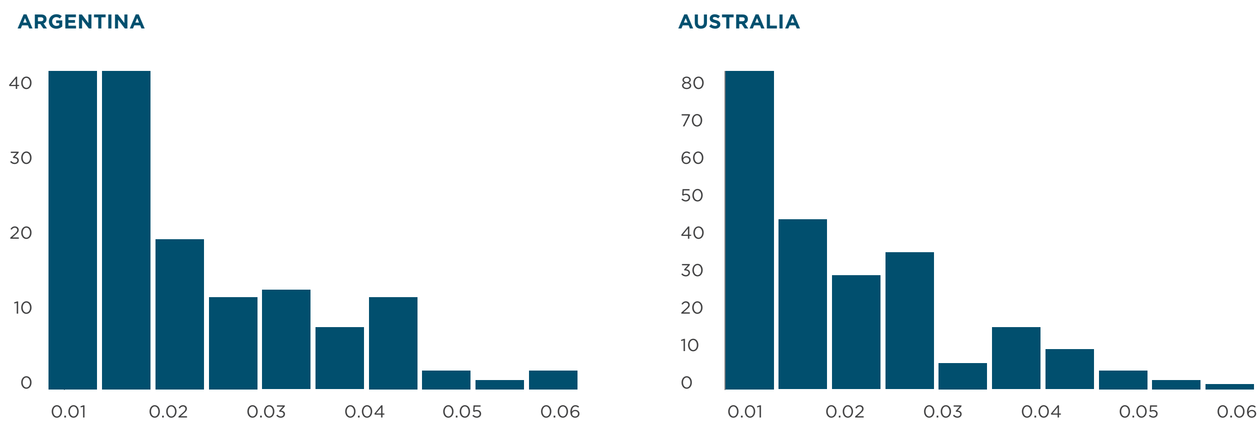
Country	Argentina	Australia	Brazil	Chile	France	India	Mexico	South Africa	UK	US
Occupations (Nodes)	166	229	206	170	228	226	192	196	244	263
Connections (Edges)	267	449	387	341	378	446	413	338	575	960
Connections per Occupation	1.6	2.0	1.9	2.0	1.7	2.0	2.2	1.7	2.4	3.7

Table 2. Network statistics

Note: All networks graphs are undirected, constructed using statistically significant pairwise correlations above 0.5 between all occupations. Edge distance represents the value of each pairwise correlation.

The degree centrality of a node describes the fraction of nodes it is connected to. Figure 2 plots the distribution of degree centrality for every node in each country. In most countries, many nodes are disconnected or connected to a handful of occupations. This is captured by the high frequency of occupations with low values of degree centrality. On the contrary a highly connected network like The United States has a more even distribution of degree centrality values.

Figure 2. Degree centrality distribution of occupation networks



[16]The index captures how over-expressed is each skill in an occupation relative to the whole economy.
[17]See the networkx package documentation.

Figure 2 (continued). Degree centrality distribution of occupation networks