Digitalization in the German Labor Market

Analyzing Demand for Digital Skills in Job Vacancies

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Foreword

The use of digital technologies already has far-reaching effects on the labor market today, and these effects will become even more pronounced in the future. On the bright side, large parts of the scientific community now agree that there will not be a mass displacement of human work by computers and robots. For Germany, it is expected that job gains and losses due to automation will balance out at least until the middle of the next decade. The crucial prerequisite for this, however, is that the workforce keeps pace with digitalization. Developing and using new hardware, software, and algorithms, analyzing big data, automating routine tasks, working remotely, mass customization in industrial production as well as the ethical handling of the new technologies are just a few examples of the substantial change in the demand for skills in the workforce. Some of the existing knowledge and skills are becoming obsolete, while the majority are still required but need to be updated. In addition, completely new skills must be acquired in order to secure a good job with decent pay, regardless of the specific type of labor contract or form of employment.

But for what exactly should workers prepare? What are the specific skills that enable them to deal with the new demands of the digital transformation? Currently, there is little information available on this. This is, of course, in part due to the great complexity of the topic. Digitalization affects the multitude of different professions and activities, industries, qualification levels and even regions in very different ways, rendering general predictions unhelpful. Moreover, digital transformation is often characterized by disruptive, exponential changes and the interaction of several simultaneous developments. These factors make quantitative forecasts based on historic trends potentially misleading. Qualitative forecasts of the future, on the other hand, must necessarily remain vague in their predictions; this applies all the more the further in the future one tries to predict.

A look at the present can be helpful here. First in the United States and more recently also in other countries, a new source of data has emerged in the form of the job advertisements that companies post on online job portals, which can substantially shed new light on the outlined question. In job advertisements, companies express their requirements for the skills of applicants. In these, employers take into account not only currently required competencies, but also competencies that will be required in the future, which employers are already anticipating today. Against this backdrop, job advertisements can offer a glimpse into the future. The fact that the majority of job advertisements are now available online makes it possible to tap into this data resource. With the help of automated scraping and linguistic text analysis as well as big data procedures for processing data sets in the double-digit millions, the skill needs of employers can be systematically analyzed and aggregated into meaningful results.

Labor market research based on the analysis of online job advertisements using big data methods is still a relatively new approach. The private research institute Burning Glass Technologies is a frontrunner in this field and has made a significant contributions to help educators in aligning programs with the market, employers and recruiters in filling positions more effectively, and policy makers in shaping strategic workforce decisions. Together with Burning Glass, the Bertelsmann Stiftung aims to promote development in these areas in Germany as well, as part of an exploratory project. The study now available – focusing on the demand for digital competences – represents the result of this cooperation.

The study focuses on a cross-sectional analysis of employer demand for digital skills in 2018, broken down by profession, industry and region. We also look at the interaction between digital skills and educational levels, gender and salary. Finally, we can also make a temporal comparison between the years 2014 and 2018.

In doing so, we have also focused on the question of what methodological challenges arise from the specifics of the German labor market and how we can deal with them. For example, there are differences in the content of job advertisements between the USA and Germany. The clearly defined basic content of occupations that are governed by the dual vocational training system in Germany means that corresponding job advertisements in this country are less detailed because only those skills that go beyond the basic skills are mentioned. The granularity of the competences described also differs. In addition, there are general methodological challenges, such as the varying intensity with which companies use online job advertisements to fill vacancies, depending on the occupational group. Finally, combining traditional and new data sources also poses a challenge. We have addressed these and other issues in the study. However, there is still a need for continued research on some points, so that methodological development must continue and we welcome suggestions in this regard.

We would like to thank the authors of Burning Glass Technologies, Layla O'Kane, Rohit Narasimhan, Julia Nania and Bledi Taska, for their great expertise and relentless effort to bring this report to fruition and our colleagues at the Bertelsmann Stiftung, Gabriel Zech, André Schleiter, Katharina Bilaine, Martin Noack and Gunvald Herdin for their valuable comments and suggestions.

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About

Burning Glass Technologies

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. For more information, visit **burning-glass.com**

Bertelsmann Stiftung

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The Bertelsmann Stiftung is committed to enabling social participation for everyone – politically, economically and culturally. The issues we address are education, democracy, Europe, health, values and the economy. In doing so, we focus on people, since only they can change the world and make it better. We share knowledge, promote expertise and develop solutions. A nonprofit foundation, the Bertelsmann Stiftung was established in 1977 by Reinhard Mohn. Visit **bertelsmann-stiftung.de**

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Executive Summary

The digitalization of occupations, and the increase in digital skills requirements across industries, has reshaped the labor market in recent decades. In this report, Burning Glass Technologies and the Bertelsmann Stiftung collaborate to understand recent trends in digitalization in the German labor market. To do so, we build a digitalization index by occupation using job postings data. This index allows for analyses of the levels and changes in the demand for digital skills in Germany in the period 2014-2018. The index includes a digital score for each occupation from 0 to 100, and, in addition to digitalization by occupation, is used to analyze digitalization by region, industry, education, gender, and salary.

Key Findings

- **Digital skills are in high demand across occupations and over time.** Across jobs of all skill levels, 79% of postings are in occupations that require digital skills.
  - ◊ The most basic digital skill, "use a computer" grew fastest at a rate of 17% in the period 2014-2018. Baseline digital skills are also the most highly requested digital skills in job postings, with 22.3% of postings calling for "use a computer" and 12.1% calling for Microsoft Office.
  - ◊ All occupation groups have increased in digitalization in the 2014-2018 period; those that were the least digital in 2014 grew in digitalization the most. Digital skills grew over time at a faster rate than non-digital skills.
- **Regional differences in digital intensity of demand are largely driven by industry composition and digital intensity by industry.** The most digitally intensive regions, including Regierungsbezirke (Administrative Districts) Oberbayern and Stuttgart, reflect high levels of digital intensity within the automotive industry. Digital intensity of demand is also high in service-oriented areas such as Regierungsbezirk Frankfurt (Main). Some industries high in digitalization in other countries, such as Health Care in the US, show below average levels of digital intensity in Germany.
- **Digitalization is correlated with various socioeconomic factors, including higher frequency of employing those with an Academic Qualification, higher salaries, and male-dominated occupations:**
  - ◊ **Academic Qualifications are associated with high levels of digitalization:** On average, the labor market employs 50% fewer people with an Academic Qualification than the most digital occupations. In contrast, the least digital occupations employ 78% fewer people with an Academic Qualification than the labor market overall.
  - ◊ **The average monthly salary for the least digital occupation is 60% lower than the average monthly salary for the most digital**

occupation. The most digital occupations enjoy a salary premium of 48% above the average occupation; the least digital occupations have an average salary 26% lower than the average occupation.

◊ **All 10 of the top most digital occupations are highly male-dominated.** No female-majority job has a digital score over 80. In contrast, in the United States, average digital scores for women are higher than those for men.[1]

Conclusions and Outlook

- Job postings data can offer valuable insights into the demand for skills by employers in an economy. **This information should be used when re-skilling workers to ensure their long-term employability** – especially those at highest risk of losing their jobs due to digitalization and automation trends.

- Most workers in the economy would benefit from learning digital skills. These are valuable across education levels and demand for them is widespread across occupations. Nevertheless, **efforts should be targeted at understanding and differentiating which digital skills would be most suitable for each education level.** Studies like ours can be used as one source of information for such a process.

- The ability to analyze skills demand on a regional level can be very valuable to governments and businesses. **Local digital skill requirements should be assessed in order to close digital skill gaps according to the specific challenges and mismatches faced by regional economies** – something that information available in job ads can help with.

- Without well-designed efforts, the benefits from digitalization may become concentrated among high-salary, highly-educated, male-dominated occupations. **Upskilling efforts in digital skills should consider groups who so far have not benefited from increased digitalization as much, including women and those without Academic Qualifications.**

1 Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. "Digitalization and the American Workforce." Brookings, November 2017. https://www.brookings.edu/wp-content/uploads/2017/11/mpp_2017nov15_digitalization_full_report.pdf

Introduction

In recent decades, technological change has reshaped the tasks performed in many occupations. One result of these task shifts has been an increase in the digital skill requirements of workers. Digitalization and digital platforms have become driving forces in the global economy widely, and in the German economy in particular.[2]

The impact of digitalization

Digitalization has become an increasingly important topic across world economies in the face of the Covid-19 pandemic. Faced by abrupt changes in the working conditions triggered by social distancing measures, many workers have been required to adapt to a more digital workplace – and Germany is no exception here. However, the digital transformation and its impact on the workforce are a broader and long-lasting trend: according to a 2019 study by the Organization for Economic Cooperation and Development (OECD), over half of all jobs in Germany are at risk of being automated or radically changed by new technologies. Complementing this with data showing that Germany ranked 29th out of 34 industrialized nations for Internet connections based on a 2017 study by the OECD, there is an indispensable need to adapt the German economy to the impacts of digitalization.

In addition to displacing workers, digitalization changes the nature of existing jobs and creates entirely new jobs. The growing share of freelance workers, e-commerce, and the so-called ‘gig economy’ have been enabled by technologies that allow for the use of remote working apps and platforms; a report on the digitalization of jobs in Europe found that over 30% of individuals sold goods or services online in Germany in 2015 based on data from the European Commission’s Digital Agenda Scoreboard.[3] New technologies also allow for the emergence of cutting-edge occupations, such as Fuel Cell Engineers or Chief Sustainability Officers.[4] Along with these changes comes a growing need for technical Science, Technology, Engineering, and Math (STEM) skills as well as basic technology skills.

Defining digitalization

Although *digitization* and *digitalization* are often used interchangeably, they have different meanings. Digitization refers to the conversion of information from analog to digital format, i.e. converting handwritten notes to a digital file. Digitalization, the focus of this report, is a much broader term that encompasses new business models, processes, and restructuring of both work and social life around digital technologies.

2 “White Paper on Digital Platforms of the Economic Affairs Ministry.” Federal Ministry for Economic Affairs and Energy, https://www.bmwi.de/Redaktion/EN/Publikationen/weissbuch-digitale-plattform-kurzfassung-eng.pdf?__blob=publicationFile&v=4

3 Berger, Thor, and Carl Benedikt Frey. “Digitalization, Jobs, and Convergence in Europe: Strategies for Closing the Skills Gap.” The European Commission, n.d., 19.

4 Berger, Thor, and Carl Benedikt Frey. “Digitalization, Jobs, and Convergence in Europe: Strategies for Closing the Skills Gap.” The European Commission, n.d., 21.

Measuring digitalization in the German labor market

In order to measure and quantify digitalization, this report looks at the demand for digital skills across occupations in Germany using job postings data. The demand for these digital skills represents investment by firms in digital technologies. Using job postings data to understand firm investment has been used in a range of previous research,[5] and allows us to proxy for the overall trend of digitalization in work and society.

Using the demand for digital skills, Burning Glass develops a digitalization index for each occupation. The index is then aggregated to each industries and regions to provide a quantitative metric describing how digitally intensive job requirements are. This is used to understand the spread of digital skills across the German labor market and to understand how digitalization has changed over time. The index is also used to assess inequality across more and less digitalized occupations in terms of educational attainment, wages, and gender.

This index builds on previous digitalization research[6] in a number of ways. Firstly, the index is based on job postings data rather than aggregate occupation-level data, allowing for a more nuanced level of understanding of digitalization by occupation since the digital skills required by each occupation can be studied. Secondly, the index is based on assessing hundreds of digital skills found in job postings rather than a small handful of digital skills. Thirdly, because job postings data represents employer demand for skills of future workers rather than the skills possessed by incumbent workers, it can shed light on future trends in the labor market with more accuracy.

5 See, e.g., Tambe, Prasanna. "Big data investment, skills, and firm value." Management Science 60, no. 6 (2014): 1452-1469; Tambe, Prasanna, Lorin M. Hitt, Daniel Rock, and Erik Brynjolfsson. "IT, AI and the Growth of Intangible Capital." Available at SSRN 3416289 (2019); Avi Goldfarb, Bledi Taska, and Florenta Teodoridis. "Could Machine Learning Be a General-Purpose Technology? Evidence from Online Job Postings?" (2019) Working Paper.

6 See, e.g., Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. "Digitalization and the American Workforce." Brookings, November 2017. https://www.brookings.edu/wp-content/uploads/2017/11/mpp_2017nov15_digitalization_full_report.pdf

Methodology

Data Sources

Job Postings Data

To create the digital index, Burning Glass mined its dataset of over 22 million job postings in Germany in 2018, the year of data used to build the primary digital index described in this report.[7] Burning Glass scrapes vacancy postings from more than 207 online job boards and company websites to collect data. In the German data for 2018, approximately 73% of job vacancy postings came from job boards or job search engines; 22% came from public employment service vacancies; and 4% came from private employment agencies. Approximately 1% of these data came from additional sources including online newspapers, classified ads portals, and individual company or employer websites. We remove duplicate postings and aggregate and use a machine-learning model to capture data from job posting text. These data include information on occupations, industries, regions, skills, and employers, with relevant taxonomies used across the European Union as seen in Table 2. The US version of this data have been used to analyze jobs and skills by a wide range of academics, including Hershbein and Kahn (2018), Deming and Kahn (2018), and Modestino et al. (2018).[8]

Job postings are useful for understanding digitalization in the labor market because they allow for a detailed, real-time look at the skills employers ask for. Using job postings data as a proxy for labor market demand comes with certain challenges. The following points should be considered when interpreting the results:

- **Distributional effects**
  There are several factors that could affect or skew the distribution of job postings, including the following:

  ◊ **Deduplication:** When job postings are collected, Burning Glass looks for duplicates across sources to ensure that job postings are not counted multiple times. Data are de-duplicated based on the text of the posting where available, and based on occupation, employer, and skills. If there is not enough information to determine if the job posting is a duplicate, the job posting remains in the dataset. In 2018, approximately 28 million raw job postings were collected, and approximately 19% were determined to be duplicates which constitutes the lower bound for the actual number of duplicates.

  ◊ **Missing jobs or missing information:** As described above, the job postings data come from job vacancy postings from job search engines, job boards, public employment service vacancies, employment agencies, individual employer websites, and some additional smaller sources that cover the available online job vacancy market. However, not all jobs are advertised in online postings, and some may be advertised in closed portals that do not allow for data collection, such as industry-specific job boards that require membership login credentials.

7 While the index is built based on 2018 data, data from 2014 is also used to assess digitalization across time

8 Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance. "Upskilling: Do Employers Demand Greater Skill When Workers Are Plentiful?" The Review of Economics and Statistics, June 4, 2019, 1–46. https://doi.org/10.1162/rest_a_00835 and Deming, David, and Lisa B. Kahn. "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals." NBER Working Paper, May 2017. https://www.nber.org/papers/w23328

◊ **One posting, many jobs:** In some cases, employers use one posting to represent multiple underlying vacancies where they expect to hire more than one person to fill roles. The data captures this as one job posting rather than many. It is difficult to measure the frequency of this effect since it is often not indicated on the job posting itself but simply known to the employer or recruiting agency.

These factors can affect the results if the resulting data is skewed toward certain occupations, industries or regions. A comparison of the data to official employment data from Eurostat, found in Appendix I, shows that the distribution of job postings across these dimensions closely matches the distribution of employment in Germany in both 2014 and 2018. This means that to the extent that these limitations effect the distribution of jobs found in the data, it is unlikely that these distributional effects meaningfully impact the results of the digital index.[9]

- **Changes over time**
  Burning Glass began collecting job postings data in Germany in 2014 and has increased the number of sources used over time to collect a larger share of available online job postings. While the absolute number of job postings has increased in this time period, the distributions look comparable. See Appendix I for a review of the distributions in comparison with employment data.

Similarly, the way in which employers choose to reference specific skills may have changed over time. This would affect the resulting data if across the board all skills showed an increase. Table 1 shows the change across years by skill categories in frequency of skill mentions.

We use two metrics to assess the change over time in skill requests. The percent of postings requesting at least one skill (section on the left side of the table) shows the percent of all job postings that request at least one digital or not digital skill in 2014 and 2018. In both years, 96.8% of postings request at least one not digital skill. In 2014, 38.1% of postings requested at least one digital skill, and in 2018, 47.5% of postings requested at least one digital skill. While there was no change in non-digital skill requests, the share of postings requesting any digital skill went up by 24.7%.

We also look at changes over time in requests by individual skill. The average rate of individual skill requests in each posting (section on the right side of the table) shows the rate at which a given skill is requested across all job postings. For example, if all digital skills were requested in only one job posting and there were 100 total job postings, then the average rate of individual skill requests for digital skills would be 1%. There was a small increase in frequency (of 11.6%) of non-digital skills and a substantial

Table 1: **Skill Data Changes Over Time**

Skill Type	Percent of Postings Requesting At Least One Skill			Average Rate of Individual Skill Requests in Each Posting		
	2014	2018	% Change	2014	2018	% Change
Not Digital	96.8%	96.8%	**0.0%**	0.18%	0.20%	**11.6%**
Digital	38.1%	47.5%	**24.7%**	0.19%	0.34%	**82.9%**

Source: Burning Glass Technologies

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9 In a dynamic economy, the correlation between the distributions of employment and demand may shift due to a reaction to shocks by demand that is different from that of employment. For example, in a recession, the distribution of demand is likely to change more than the distribution of employment.

increase in rate of requests per job posting (82.9%) of digital skills. This shows that our analyses regarding changes of digital skill requests over time are largely not driven by an increase overall in the skills requested in job postings over time.

- **Implicit skills and employer preferences:** Job postings are the best information available to understand employer preferences and demand. However, not all employers write job postings that include the most important or preferable skills for the vacancy. Furthermore, many job postings have skills that are implicit; if a job posting mentions "computer programming" the basic ability to "use a computer" is also implied to be a requirement. Other examples of implicit skills include "Excel" implies "use spreadsheets"; "manage sales teams" implies "supervise sales activities"; and "Pandas", a package used in the programming language Python, implies "Python". These implicit skills may also mean that demand for basic skills such as "use a computer" are under-estimated.

While the data analysis relies on explicit skills and does not account for implicit skills, accounting for additional implicit skills would result in the most digital jobs looking even more digital, since knowing advanced digital skills such as "computer programming" requires a full spectrum of digital skills as well. Because of this, the digital index can be thought of as a conservative measure of the digitalization of the occupations with implied digital skills.

Comparison of the distribution of occupations and industries in the Burning Glass data and in survey data in Germany shows that the distributions are highly correlated.[10] This means that, despite these limitations, there is confidence that the results of the digital index are not being heavily biased.

European Labour Force Survey — Germany

In addition to Burning Glass data, this report also uses data from the European Labour Force Survey for Germany (LFS)[11] to understand the distribution across occupations of education levels, gender, and salary information, and to connect this to the digital index. The LFS uses the German Classification of Occupations (KldB)[12] for Occupation taxonomy and the International Standard Classification of Education (ISCED)[13] for education taxonomy.

Table 2: **Burning Glass German Data Elements and Associated Taxonomies**

Name	Taxonomy
Occupation	ESCO Level 4
Occupation Group	ESCO Level 1
Industry	NACE Level 1
Region	NUTS 2
Area	NUTS 3
Skill Type	Burning Glass Skill Types[a]
Skills	ESCO Skills & Stack Overflow Skills

Source: Burning Glass Technologies | BertelsmannStiftung

a See page 14 for a complete list of skill types

10 See Appendix I for a full comparison.
11 "EU Labour Force Survey – Data and Publication - Statistics Explained." Accessed October 1, 2019. https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_labour_force_survey_%E2%80%93_data_and_publication
12 "KldB 2010 - Classification of Occupations, Issue 2010." Accessed October 1, 2019. https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=kldb2010&lang=EN
13 "International Standard Classification of Education (ISCED)," March 16, 2017. http://uis.unesco.org/en/topic/international-standard-classification-education-isced

In order to match KldB occupations used by the LFS data to European Standard Classification of Occupations (ESCO) occupations used by Burning Glass data, a crosswalk was created based on a sample of postings. A complete methodology for developing this crosswalk can be found in Appendix I.

Taxonomy Descriptions and Limitations

ESCO Taxonomy

The Burning Glass Germany database relies on the ESCO taxonomy for Occupations (ESCO Level 4), Occupation Groups (ESCO Level 1), and Skills (ESCO Skills). This taxonomy was built to provide a common language to help jobseekers find jobs that match their skills, connect employment and education providers, and connect labor markets across the European Union.[14]

The ESCO Occupation taxonomy covers 436 unique occupations (ESCO Level 4). Of these, 425 appear in job postings data. For robustness, this report considers only occupations with at least 1,200 job postings in 2018 so as not to rely on small sample sizes. This brings the total number of occupations in the analysis to 330. The ESCO taxonomy is consistent with the International Standard Classification of Occupations (ISCO-8) created by the International Labour Organization. This includes a four-level hierarchy with 10 major groups of occupations in ESCO Level 1.[15]

The ESCO Skills taxonomy covers 13,485 unique skills, competences, and knowledge. For use in job postings data, the taxonomy suffers from two primary limitations. The first is that many of the skills in the taxonomy do not align with the language used in job postings. For example, some skills that appear in the taxonomy but do not appear in job postings include "apply anti-oppressive practices" (too broad) and "adjust envelope cutting-settings" (too specific). Because of this, only 3,111 of the 13,485 ESCO skills appear in job postings.

The second limitation of the ESCO taxonomy is that it is not hierarchical and does not cluster similar skills. For example, the skills "use spreadsheets" and "use spreadsheets software" exist separately. It also features both specific software skills and the broader group of skills to which they belong: "computer programming" and types of computer programming such as "Python" and "Java" coexist. Although we are aware of these limitations, we have not made any alterations to the official ESCO taxonomy in this research. In order to stay consistent with ESCO taxonomy, we refer to unique ESCO skills as unique or separate skills, even if implicit in those skills are clusters or groups of skills.

In order to augment ESCO skills taxonomy with additional relevant digital skills, the job postings data is also tagged with skills tags from Stack Overflow.[16] These include standard productivity software skills such as "Microsoft Excel" and "Microsoft Word" as well as cutting-edge technology skills such as "blockchain". These skills are also considered unique skills in the analysis.

NACE Taxonomy

The NACE (Statistical classification of economic activities in the European Community) taxonomy is the classification of economic activities or industries in the European Union.[17]

NUTS Taxonomy

The NUTS (Nomenclature des Unités territoriales statistiques) classification is standardized across all

14 "European Classification of Skills, Competences, Occupations and Qualifications (ESCO)." SKILLS FOR EMPLOYMENT - Knowledge sharing platform. Accessed October 1, 2019. http://www.skillsforemployment.org/KSP/en/Details/?dn=WCMSTEST4_191899

15 "ISCO - International Standard Classification of Occupations." Accessed October 31, 2019. https://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm

16 These skills come from posts on https://stackoverflow.com, which is an open community to share knowledge on computer programming and coding as well as other technologies.

17 "NACE Background - Statistics Explained." Accessed October 1, 2019. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=NACE_background

EU countries to enable cross-country comparison. The classification is divided into four hierarchical levels: NUTS 0, NUTS 1, NUTS 2, and NUTS 3. In Germany, NUTS 0 regions refers to the country; NUTS 1 correspond to federal States (Bundesländer); NUTS 2 regions correspond to regions, specifically Regierungsbezirke and Stadtstaaten; and NUTS 3 areas are generally districts known as Landkreise or as kreisfreie Städte.[18]

Measuring Digitalization

The first step in building the digital index was to assess the percentage of postings per occupation calling for a digital skill. There are five types of skills, as outlined in Table 3. The skills were labeled as belonging to each skill type using an expert approach where labor market experts classify each skill manually.[19] Each skill type was assigned

Table 3: **Skill Types**

Skill Type	Skill Description	Number of Unique Skills	Skill Examples	Weight[a]
Not Digital		2,528	Adapt to change Project management Work as a team	0
Basic Information Skills	Ability to use IT tools in daily work, regardless of the company function to which they belong	25	Use a computer Microsoft Office Manage digital documents	1
Information Brokerage Skills	Ability to use IT tools for communication and collaboration	70	Carry out internet research Microsoft SharePoint Use online tools to collaborate	1
Applied and Management Information Skills	Ability to use tools and software needed by people within an organization supporting management in both operational and decision-making processes	201	Salesforce Microsoft Access Web analytics	1.5
Information and Computer Technology (ICT) Technical Skills	Strong technological skills on solutions, platforms, and programming languages that characterize people working within the ICT structures of public and private organizations	287	Computer programming CSS Administer ICT system	2

Source: Burning Glass Technologies

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a The same weight was used for both Basic Information Skills and Information Brokerage Skills to reflect comparable levels of time required to learn these skills. Sensitivity analyses were conducted to ensure the chosen weights did not bias the results. The full sensitivity analyses are shown in Appendix I.

18 "NUTS Classification - Statistisches Bundesamt." Accessed October 1, 2019. https://www.destatis.de/Europa/EN/Methods/Classifications/OverviewClassification_NUTS.html
19 This methodology is described in more detail here: Colombo, Emilio, Fabio Mercorio, and Mario Mezzanzanica. "AI Meets Labor Market: Exploring the Link Between Automation and Skills," October 2018. https://dipartimenti.unicatt.it/diseis-wp_1802.pdf

a weight from 0 (Not Digital) to 2 (Information and Computer Technology Technical Skills) based on the level of technical skill required. Assigning weights to different skill types allows the index to take into account the difference in level of investment in terms of learning time required for each skill type. The percentage of postings calling for a digital skill by occupation was then aggregated and weighted by skill type. The remaining score was then normalized to be between 0 and 100.

For example, take the occupation "Web and multimedia developers". Some of the most common skills are "computer programming" (Information and Computer Technology skill, appears in 71% of postings); "implement front-end website design" (Information and Computer Technology skill, appears in 45% of postings); and "analyse software specifications" (Applied and Management Information skill, appears in 39% of postings). Assume for a moment that these are the only skills for this occupation. To calculate the index, the percentage that each skill appears in postings for the occupation is multiplied by the skill type weight and then summed: (0.71*2)+(0.45*2)+(0.39*1.5) = 2.91. Each occupation is given a score in this manner. Then, the scores are re-weighted to be between 0 and 100.

This methodology has several benefits. First, using postings data allows for an understanding of digital skill demand rather than the more typically studied supply of digital skills or the skills of incumbent workers. This allows for a more future-looking approach to digital skills, since these skills are those employers wish to have going forward. Second, using a rich database of over 22 million job postings and almost 600 digital skills allows for robust analysis of digitalization across the entire range of occupations. Third, assigning different weights to different types of digital skills allows for the digital index to take into account the difference in investment (of time and/or money) required between, for example, learning how to use Microsoft Office and learning how to code in CSS. Fourth, normalizing the index to be between 0 and 100 allows for intuitive comparison of digitalization across occupations.

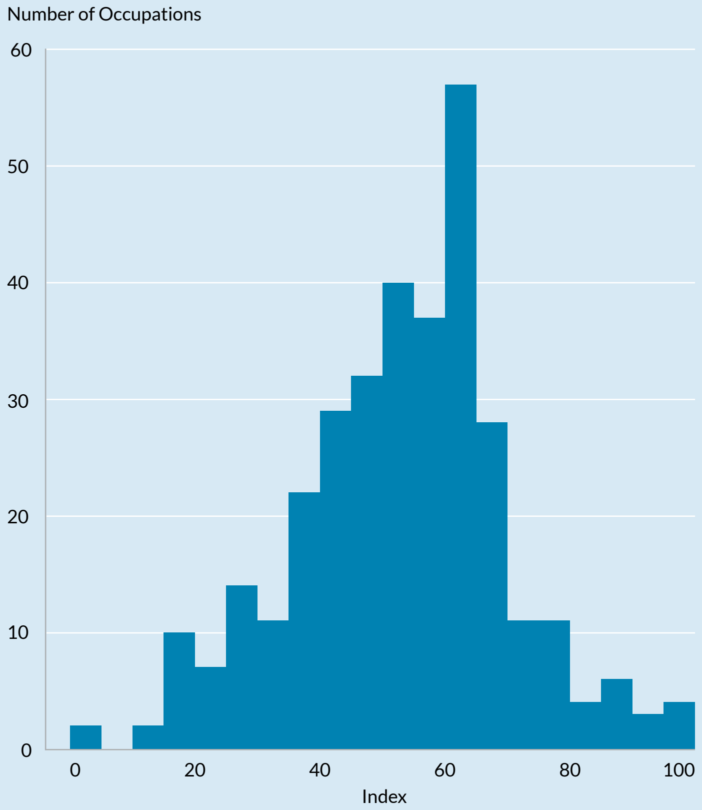
It should be noted that the index should be interpreted as an ordinal rather than cardinal; that is, while the index can help understand the digitalization of occupations relative to others, the precise numeric scores assigned to each occupation do not themselves carry innate meaning. Small differences in digitalization score do not indicate meaningful differences in digitalization, but rather the score can help understand which occupations have undergone the most digitalization and which the least, with some reference points in between. For this reason, throughout the report the focus will be on the most and least digital occupations rather than on comparing individual occupations to each other. In further sections of this report, we compare digitalization indices over time. These comparisons are similarly based on the direction of the change over time, and a change from a digital index of 20 in 2014 to a digital index of 40 in 2018 should not necessarily be interpreted as an occupation becoming twice as digital over this time period.

Another limitation of this methodology is that it does not account for differences in digitalization within an occupation across regions or industries. Instead, the analyses presented by region and industry use the national occupation level digital index without differentiation by location or industry. This means that if there are differences within an occupation across location (for example, if Accountants in one area of Germany use more digital skills than Accountants in others) or across industry (for example, if Administrative assistants in one industry use more digital skills than in another industry) these differences will not be accounted for. This also means that the differentiation in intensity of digital demand by region and location are likely a lower bound for the true variation across these factors.

The Digital Index

This section explores the results of the occupation level digital index and compares the findings to those in the U.S. The index measures the level of digitalization in each occupation, and forms the basis of the analyses throughout the report.[20]

Figure 1: **Digital Index Distribution**



Source: Burning Glass Technologies

BertelsmannStiftung

Figure 1 shows the distribution of the digital index. Most occupations have a digital index between 37 and 80. There are a high number of occupations concentrated in the middle of the distribution, with a digital index between 57 and 62. The index is slightly skewed to the right, with more occupations showing a digital index of greater than 50 than below 50, and specifically more occupations between 80 and 100 than between 0 and 20.

Table 4 depicts the top 10 most digital occupations according to the digital index. As is expected, all of the most digital occupations are highly technical computing jobs, including developers, programmers, technicians, and other database and network professionals. These occupations involve not only relying on digital technologies for productivity, but also the creation, development, and maintenance of digital technologies themselves. These jobs are comparable to the highly digital jobs found by the Brookings Institution based on US data: Software Developers, Applications; Computer Systems Analysts; and Financial Analysts.[21]

20 The complete occupation level digital index can be found in Appendix IV

21 Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. "Digitalization And The American Workforce." Brookings, November 2017. https://www.brookings.edu/wp-content/uploads/2017/11/mpp_2017nov15_digitalization_full_report.pdf

Table 4: **Most Digital Occupations**

Index	Occupation
100	Web and multimedia developers
98	Web technicians
97	Database designers and administrators
96	Systems administrators
95	Database and network professionals not elsewhere classified
95	Software developers
91	Computer network professionals
89	Applications programmers
89	Software and applications developers and analysts not elsewhere classified
89	Systems analysts

Source: Burning Glass Technologies | BertelsmannStiftung

Table 5 shows median digital occupations based on the digital index. The middle of the distribution shows a wider range of types of digital jobs, and are largely those that are likely to use digital skills that are specific to their field.

Table 5: **Median Digital Occupations**

Index	Occupation
56	Veterinarians
55	Chemical engineers
55	Laundry machine operators
55	Transport clerks
54	Bicycle and related repairers
54	Clearing and forwarding agents
54	Insurance representatives
54	Paper products machine operators
54	Sales demonstrators
54	Sewing machine operators

Source: Burning Glass Technologies | BertelsmannStiftung

Table 6 shows the least digital occupations based on the digital index. This includes service workers (Domestic housekeepers, Cleaners and helpers in offices, Kitchen helpers, Hairdressers); construction and logistics workers (Bricklayers and related workers, Heavy truck and lorry drivers, Cabinet-markers and related workers, and Food and related products machine operators); and early childhood teachers (Elementary workers not elsewhere classified, Early childhood educators). These results are comparable to the occupations found to have a low digital skill score in the US, which include Cooks, Construction Laborers, and Personal Care Aides.[22]

Table 6: **Least Digital Occupations**

Index	Occupation
19	Early childhood educators
19	Food and related products machine operators
18	Elementary workers not elsewhere classified
18	Hairdressers
18	Kitchen helpers
17	Cabinet-makers and related workers
13	Domestic housekeepers
11	Heavy truck and lorry drivers
2	Bricklayers and related workers
0	Cleaners and helpers in offices, hotels and other establishments

Source: Burning Glass Technologies | BertelsmannStiftung

The results of the digital index at the occupation level are intuitive and provide evidence in favor of the validity of the index's construction. As expected, occupations that require *creating* digital technologies come out on top; occupations that require *using* digital technologies are in the middle; and occupations that *rarely* require digital technology appear as the least digital occupations.

22 Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. "Digitalization And The American Workforce." Brookings, November 2017. https://www.brookings.edu/wp-content/uploads/2017/11/mpp_2017nov15_digitalization_full_report.pdf

Key Findings

Digital Skills are in High Demand Across Occupations and Over Time

This section explores the breadth and depth of digital skill permeation across occupations in the German economy and unpacks trends in digitalization over time. Digital skills are in high demand across occupations in Germany. In order to analyze occupations across skill levels, an occupation was considered to *require digital skills* if it had a digital index above 33. This threshold was chosen based on empirical observations of the distribution of the digital index and on the threshold chosen by Muro et al for the U.S. Sensitivity analyses showed on average changes of less than approximately 5% by increasing or decreasing the threshold by 5 points. Across jobs of all skill levels, 79% of postings are in occupations that require digital skills.

Table 7: **Digital Intensity Across Skill Levels**

Job Skill Level	% of Job Postings in Occupations Requiring Digital Skills[a]
Low-Skill[b]	61.5%
Middle-Skill	79.5%
High-Skill	94.4%
All Jobs	78.5%

Source: Burning Glass Technologies | BertelsmannStiftung

a An occupation was considered to require digital skills if it had a digital index above 33.
b Since the database contains fewer low-skill job postings as compared to employment, and since the low-skill jobs that are posted online are more likely to be digitally intensive than those that are not posted online, the demand for digital skills may be overestimated.

Digital Skills Permeate All Qualification Levels

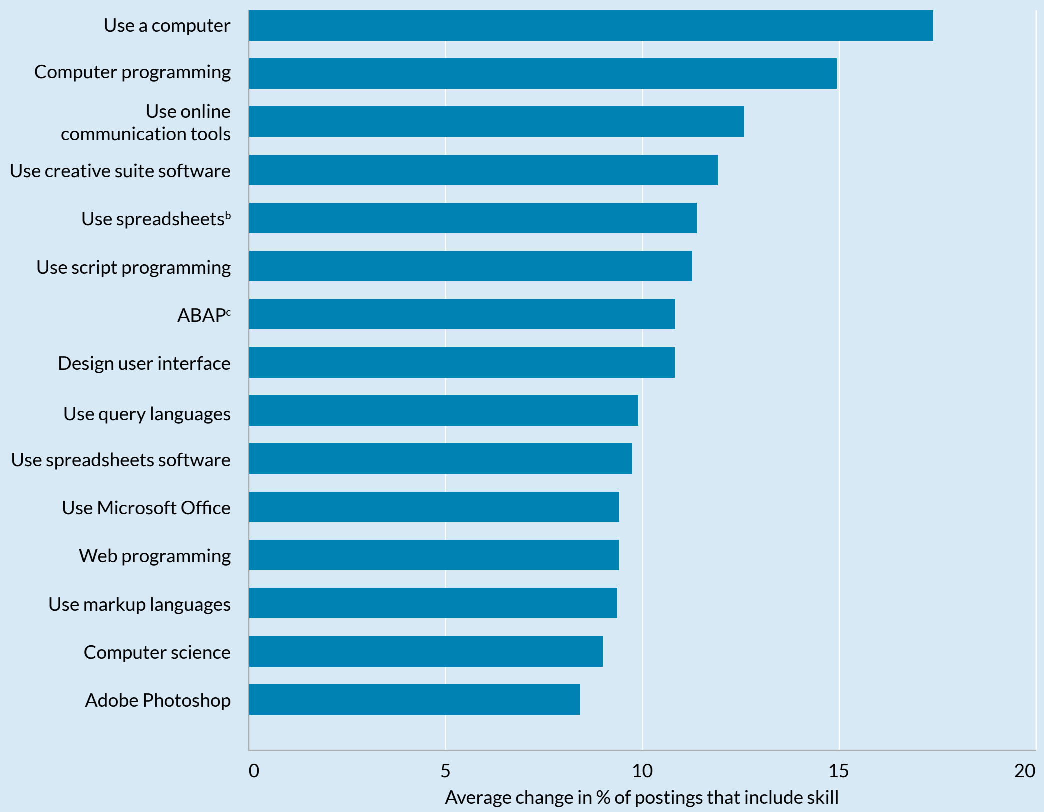
Demand for digital skills is high across all qualification levels.[23] Among low-skill jobs, 62% of job postings are in occupations that require digital skills, and among high-skill jobs, 94% of postings are in occupations that require digital skills. This illustrates that digital skill demand is not limited to only high- and middle-skill occupations. These findings mirror those found by Burning Glass in the UK, where 82% of job postings across all jobs are in occupations that require digital skills.[24] Table 7 shows the percent of job postings in occupations requiring digital skills across different skill levels.

Baseline Digital Skills are Increasingly Important Across Occupations

While specific and highly technical digital skills will continue to be important for the most digital occupations, baseline digital skills grow fastest across all occupations in the German economy. "Use a computer", the most basic digital skill, showed the highest digital skill growth between 2014 and 2018 of approximately 17%. Of the top five fastest growing digital skills, three are baseline

23 The skill levels are defined at the occupation level as low-skill (ESCO groups 1-3); middle-skill (ESCO groups 4-6) and high-skill (ESCO groups 7-9).
24 Nania, Julia, Hal Bonella, Dan Restuccia, and Bledi Taska. "No Longer Optional: Employer Demand for Digital Skills." Burning Glass Technologies, June 2019. https://www.burning-glass.com/wp-content/uploads/no_longer_optional_report.pdf

Figure 2: **Digital Skill Growth 2014-2018**[a, b, c]



Source: Burning Glass Technologies | BertelsmannStiftung

a Newer skills such as Blockchain or Hadoop do not appear because 2014 is used as a base, and many of these skills appeared more recently.
b As noted in the methodology section, the ESCO taxonomy is not hierarchical and includes skills that overlap, which can be seen here, such as "use spreadsheets" and "use spreadsheets software".
c ABAP stands for Advanced Business Application Programming and is a high-level programming language.

digital skills: "use a computer" (17.3%), "use creative suite software" (11.8%), and "use online communication tools" (12.5%). These skills are increasingly relevant across all occupations.

Similarly, the most highly requested digital skills are baseline digital skills. By far, the most frequent skill requested is "use a computer" (22.3%) followed by "use Microsoft office" (12.1%). These skills are also requested in a high number of occupations: 318 and 211 out of the total 425 occupations, respectively.[25]

This implies that these skills are versatile and transferable across occupations. Specialized and highly technical digital skills are requested in far fewer postings across occupations, with computer science and computer programming requested in approximately 4% of postings, and only requested in 129 and 59 occupations, respectively. Table 8 shows the top most highly requested digital skills across occupations in 2018.

25 A skill was considered requested in an occupation if it was requested in at least 1% of postings for that occupation. Using a threshold between 0.5% and 1.5% of postings resulted in a change in occupation count of less than 5%.

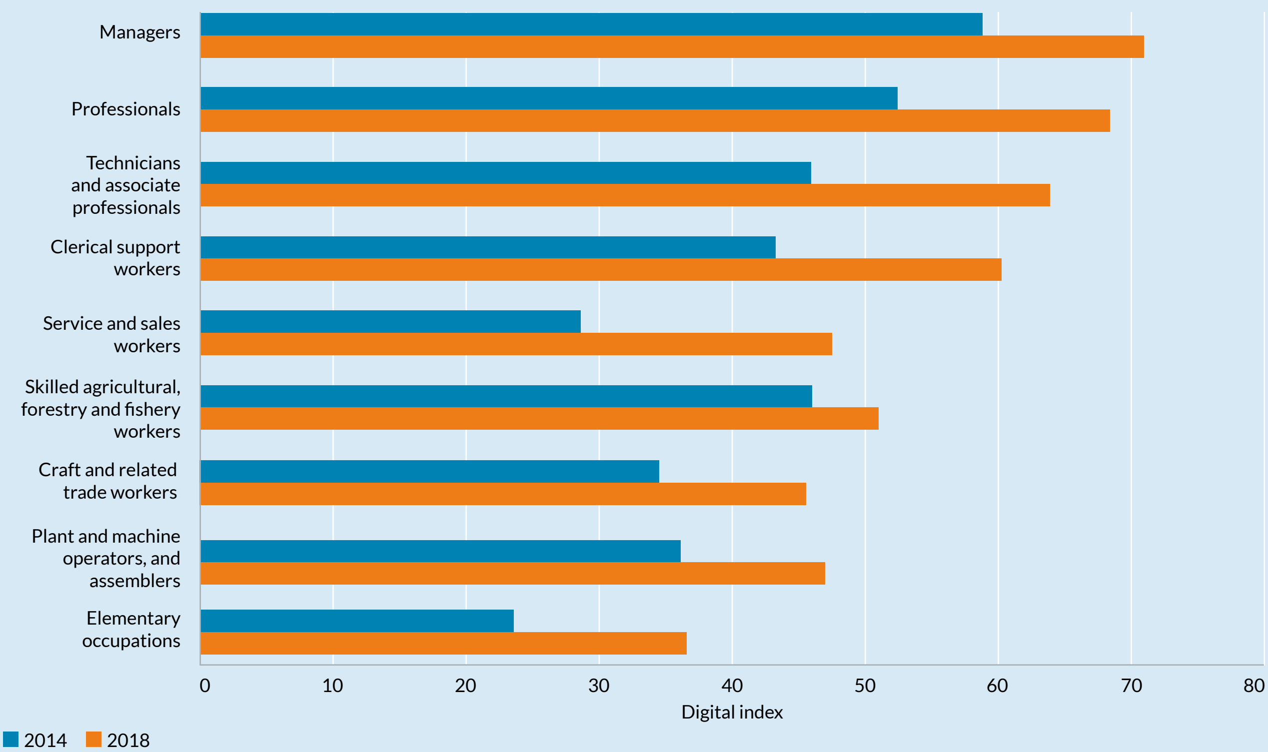
Table 8: **Top Digital Skills Requested in Job Postings in 2018**

Skill	% Job Postings Requesting Skill	Number of Occupations in which Skill is Requested (Total 425)
Use a computer	22.3%	318
Use Microsoft office	12.1%	211
Office software	7.4%	264
Use spreadsheets	5.6%	189
Use online communication tools	5.0%	151
Excel	4.0%	223
Computer programming	3.9%	59
Computer science	3.8%	129
Administer ICT system	3.5%	24
Database	3.4%	127

Source: Burning Glass Technologies

| BertelsmannStiftung

Figure 3: **Change in Digital Index 2014-2018 by Occupation Group (ESCO Level 1)**



Source: Burning Glass Technologies

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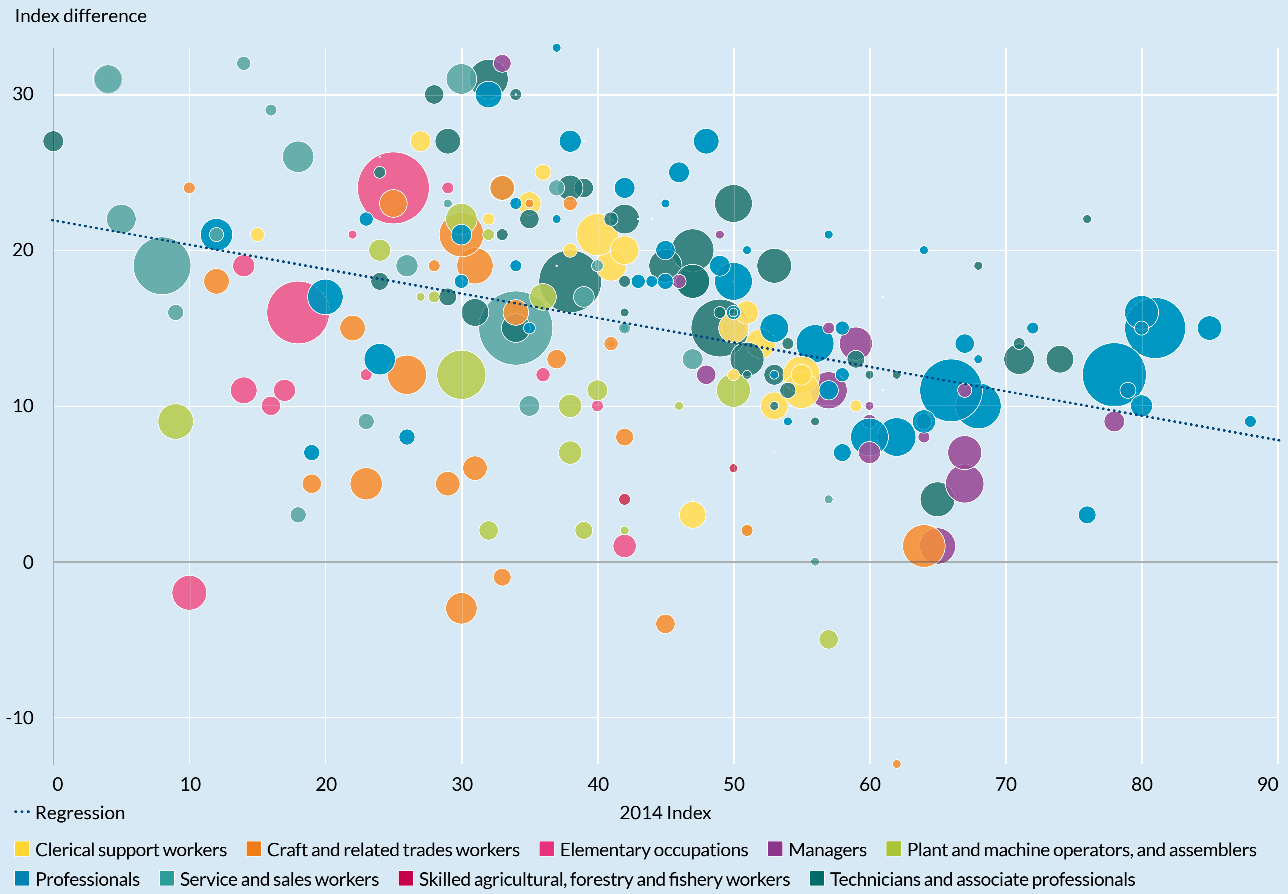
Digital Skills are Increasing in Importance Over Time

The importance of digital skills has been increasing over time. Figure 3 shows the change in digital index from 2014 to 2018 by occupation group.[26] In every occupation group, the digital index has increased from 2014 to 2018. This trend also holds by industry and region, which indicates that the increase in digitalization is not limited to a small number of groups, but rather is widespread across the German economy.[27]

Not only have occupations increased in digitalization since 2014, they have also done so at a pace that varies with digital skill intensity. Figure 4 plots the change in digital index between 2014 and 2018 against the digital index in 2014. Each bubble represents an occupation (ESCO Level 4), the color of the bubble is based on an occupation group (ESCO Level 1), and the size of the bubbles corresponds to the demand (number of job postings) for that occupation in 2018. The downward sloping line indicates that the change in index between 2014 and 2018 was higher for occupations with a lower digital index in 2014.

Figure 4: **2014 Index vs. Change in Index, by Occupation Group**



Note: Each bubble represents an occupation (ESCO Level 4), the color of the bubble is based on an occupation group (ESCO Level 1), and the size of the bubbles corresponds to the demand (number of job postings) for that occupation in 2018.

Source: Burning Glass Technologies

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26 The 2014 digital index is scaled to be in terms of the 2018 index for accurate comparison. As noted in the description of the index, interpretation of the changes over time of the digital index should focus on the direction of the change. While the index allows for comparison over time in direction, an index of 20 in 2014 and 40 in 2018 does not necessarily indicate a doubling of digitalization, but does represent an increase.

27 See Appendix II for figures by region and by industry.

Example: Construction supervisors

One example of an occupation that has seen substantial growth in digitalization from 2014 to 2018 is Construction supervisors. In 2014, Construction supervisors had a digital index of 29, which is quite low in the distribution, whereas in 2018 Construction supervisors had a digital index of 56, in the middle of the distribution. This is driven in part by increases in demand for technical software skills, such as "use technical drawing software" which was demanded in less than 0.2% of postings in 2014 and increased to 2% of postings in 2018. Similar increases occurred for "autocad", "graphics editor software", and "creative suite software".

This finding intuitively makes sense: Occupations that had more room to become digitally intensive experienced higher growth in digitalization. This trend indicates that digitalization is not just happening among occupations that are already very digital, but rather is happening fastest for occupations that are less digital.

Digital Intensity of Demand Across Regions Mirrors Industry Composition

This section explores differences in digital intensity across regions. The regional digital index is constructed by applying the occupation level digital index to the distribution of occupations in the region based on official employment data.

For each region, at the NUTS 2 or NUTS 3 level, the digital index by occupation is weighted by the employment for each occupation to construct an average score that gives an indication of the digital intensity of demand in the region. For example, if region A has higher levels of employment in more digital occupations as compared to region B, then region A will have a higher score, indicating that the skills demand across occupations in that region is more digitally intensive.

However, this score does not capture differentiation in digitalization within an occupation across regions since the digital index is based on aggregated national averages. For example, if job ads for a same occupation require digital skills more intensively in region A than in region B, this differentiation is not reflected in the analysis. We have used employment data to understand the distribution of occupations instead of directly using job ad data to do so because of sparsity in job ad data at local job market levels – especially in NUTS 3 regions. Therefore, this methodology provides an approximation to regional demand measurement as close as possible to a direct analysis.

Nevertheless, the employment distribution is highly correlated with demand when using a Pearson correlation, as demonstrated in Appendix I in more detail. Also, since the digital index is created using job postings data that allows us to understand the composition of skills, or future skills, in an occupation, the digital index itself at occupation level measures digital intensity of demand. This section therefore does provide valuable insight into the distribution of more and less digital occupations across regions and so we refer to it as "digital intensity of demand" from here onwards.

The data used in the maps of this section connects data from the Burning Glass German database to data from the December 2018 European Labour Force Survey (LFS)[28] for Germany to understand the distribution across occupations by region. To use this data alongside the digitalization index, the occupations found in the LFS were mapped to the ESCO occupations. In order to match the German Classification of Occupations (KldB)[29] used by the LFS data to ESCO occupations used by Burning Glass data, a crosswalk was created based on a sample of postings. A complete methodology for developing this crosswalk can be found in Appendix I.

Figure 5 shows digital intensity of demand in Germany at the NUTS 2 level (Regierungsbezirke). The most digitally intensive regions are Oberbayern, Stuttgart, Darmstadt, and Hamburg. This reflects the strong presence of digital skill demand within the automotive industry, especially in the south of Germany, as well as the logistics and media sectors. The least digitally intensive regions are Mecklenburg-Vorpommern, Trier, and Lüneburg.

Assessing digital intensity of demand at the NUTS 3 level allows for a deeper understanding of the differences within regions. Within one of the most digitally intensive regions, Regierungsbezirk

Figure 5: **Digital Intensity of Demand in Germany, by NUTS 2**

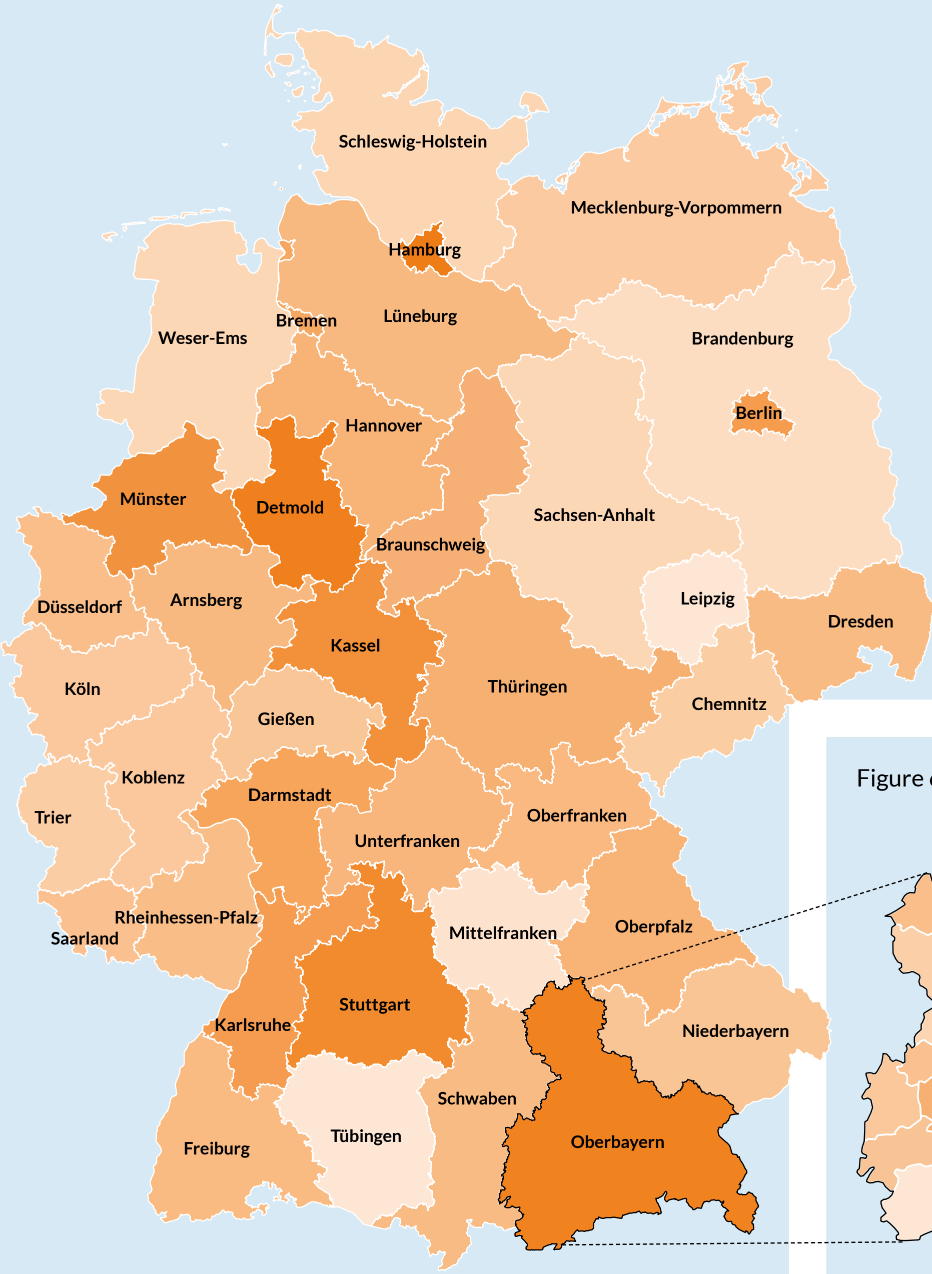
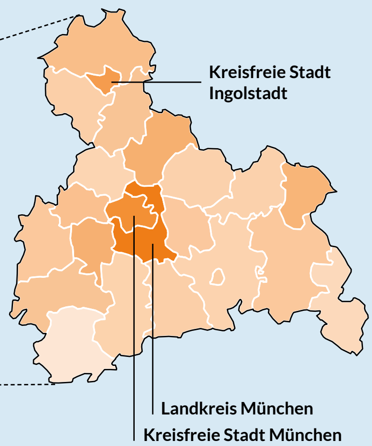


Figure 6: **Digital Intensity of Demand in Oberbayern**



Source: Burning Glass Technologies

BertelsmannStiftung

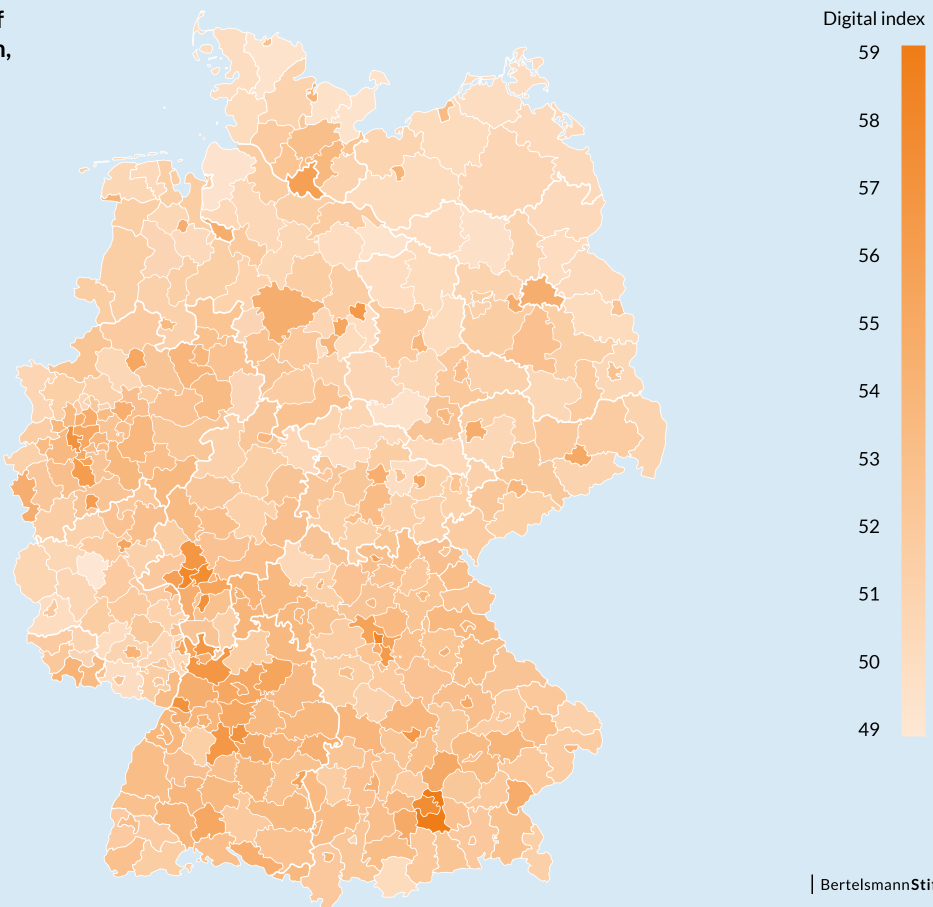
28 "EU Labour Force Survey – Data and Publication - Statistics Explained." Accessed October 1, 2019. https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_labour_force_survey_%E2%80%93_data_and_publication

29 "KldB 2010 - Classification of Occupations, Issue 2010." Accessed October 1, 2019. https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=kldb2010&lang=EN

Oberbayern, there is a distribution of digital intensity of demand as shown in Figure 6. The most digitally intensive are Landkreis München (digital intensity score of 59); Kreisfreie Stadt München (digital intensity score of 58); and Ingolstadt, Kreisfrei Stadt (digital intensity score of 57). These three areas also come out on top according to the Zukunftsatlas (Atlas of the future), a ranking that evaluates an area's readiness for the future,[30] showing how digital intensity of demand can play a vital role in an area's success.

A closer look at digital intensity of demand at the NUTS 3 level can help unpack regional specialization. Take, for example, two of the most digitally intensive areas at the NUTS 3 level, for which a demand analysis directly using job ad data is possible. Both Frankfurt am Main and Ingolstadt are highly digitally intensive areas, with digital intensity scores of 58 and 57, respectively. However, the occupation distribution within each area points to different digital skill prevalence. Both areas have high demand for systems analysts and software developers, two highly digital occupations. As seen in Table 9, Frankfurt's economy is driven by the services industry. A high proportion of international companies are represented in the city, as well as the German stock exchange and the European Central Bank being based in the largest financial center in the Eurozone. The list of occupations in high demand reflects that fact by showing many more service and business-oriented digital occupations, including Management and organization analysts, Advertising and marketing professionals, Business services and administration managers, and Administrative and executive secretaries. In contrast, as specified in Table 10, Ingolstadt has a higher focus on engineering and manufacturing. Ingolstadt is an example for a local manufacturing cluster centered around a relatively small town with excellent transport links to adjacent areas. There is a high prevalence of Engineering professionals, Mechanical engineers, Manufacturing labourers, Electrical engineering technicians, and Motor vehicle mechanics and repairers.

Figure 7: **Digital Intensity of Demand by Region, NUTS 3**



Source: Burning Glass Technologies

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Table 9: **Most Demanded Occupations, Frankfurt (Main)**

Occupation	% of Demand in Frankfurt	Index	% of Demand in Ingolstadt
Systems analysts	6.4%	89	3.8%
Software developers	4.0%	95	6.2%
Engineering professionals not elsewhere classified	3.1%	75	7.9%
Administrative and executive secretaries	3.0%	61	1.9%
Shop sales assistants	2.5%	44	4.0%
Management and organization analysts	2.5%	65	1.2%
Manufacturing labourers not elsewhere classified	2.2%	44	2.1%
Advertising and marketing professionals	2.2%	76	0.9%
Business services and administration managers not elsewhere classified	1.9%	65	1.3%
Life science technicians (excluding medical)	1.9%	52	2.4%
Accountants	1.6%	67	0.7%
Research and development managers	1.5%	70	0.6%
Retail and wholesale trade managers	1.4%	70	1.0%
Enquiry clerks	1.4%	57	0.8%
Accounting associate professionals	1.4%	60	0.7%

Source: Burning Glass Technologies

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Table 10: **Most Demanded Occupations, Ingolstadt**

Occupation	% of Demand in Ingolstadt	Index	% of Demand in Frankfurt
Engineering professionals not elsewhere classified	7.9%	75	3.1%
Software developers	6.2%	95	4.0%
Shop sales assistants	4.0%	43	2.5%
Systems analysts	3.8%	88	6.4%
Life science technicians (excluding medical)	2.4%	49	1.9%
Mechanical engineers	2.2%	64	0.8%
Manufacturing labourers not elsewhere classified	2.1%	44	2.2%
Administrative and executive secretaries	1.9%	56	3.0%
Freight handlers	1.8%	27	1.1%
Clerical support workers not elsewhere classified	1.7%	62	1.1%
Electrical engineering technicians	1.4%	63	0.7%
Industrial and production engineers	1.4%	67	0.8%
Motor vehicle mechanics and repairers	1.3%	32	0.5%
Health care assistants	1.3%	20	0.7%
Business services and administration managers not elsewhere classified	1.3%	63	1.9%

Source: Burning Glass Technologies

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30 The ranking looks at various aspects including competitiveness, welfare, innovation, labor market, and demography of an area. For more information, please see https://www.prognos.com/publikationen/zukunftsatlas-r-regionen/zukunftsatlas-2019/

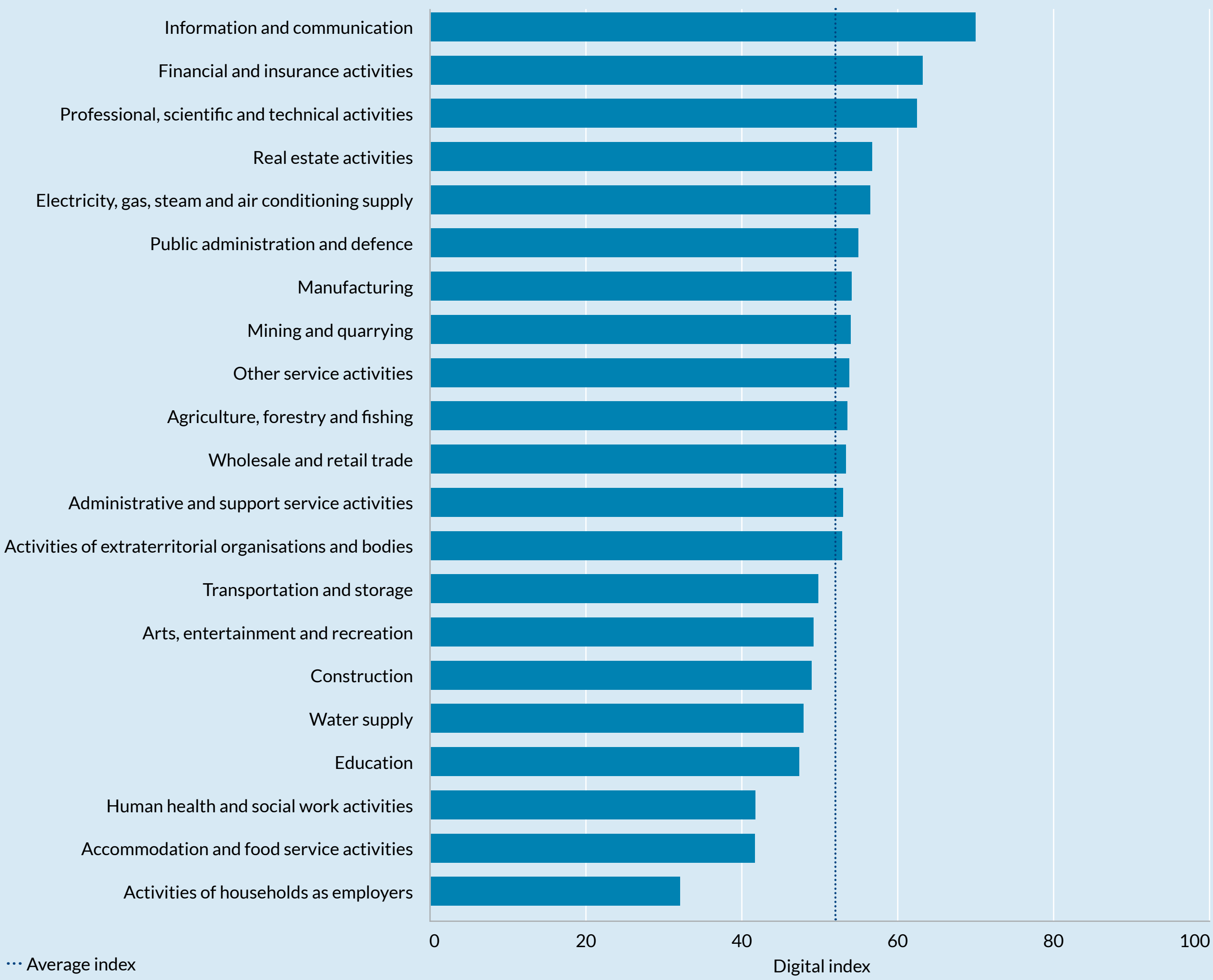
Digital Intensity of Demand by Industry

Digital intensity of demand also shows clear differences across industries (NACE Level 1). Burning Glass assigns each job posting to an industry using a machine learning model that maps the employer of the job posting to an industry.[31]

Similarly to region, for each industry, the digital index by occupation is weighted by the occupation distribution in each industry to construct an average score that reflects the digital intensity of demand in the industry. Industries with high representation of more digital occupations thus will have higher digital intensity scores. This score does not capture differentiation in digitalization within an occupation across industries. However, this metric does take into account differences in the prevalence of digital skills based on the occupation distribution within each industry. This can be thought of as a lower bound of digital variation by industry: if it is the case that occupations also vary in digital intensity across industries, this would increase the variation by industry in digital score.

31 For more information on the data labeling process, see pages 36–41 of "Big Data for Labour Market Intelligence: An Introductory Guide", European Training Foundation, https://www.etf.europa.eu/sites/default/files/2019-06/Big%20data%20for%20LMI.pdf

Figure 8: **Digital Intensity of Demand by Industry**



Source: Burning Glass Technologies

BertelsmannStiftung

The most digitally intensive industries are Information and communication; Financial and insurance activities; and Professional, scientific and technical activities. Other above-average industries in terms of digital intensity include Manufacturing; Mining and quarrying; and Real estate activities. The least digitally intensive industries are Education; Accommodation and food service activities; Human health and social work activities; and Activities of households as employers. In contrast to these findings in Germany, a Brookings report on digitalization in the US showed digitalization in the Health Care industry to be substantially above average, and digitalization in Manufacturing to be below average.[32] While German manufacturing may be ahead of other countries in terms of digital intensity, other sectors that are highly digital in other economies still lag behind.

Digitalization and Socioeconomic Factors

This section explores the relationship between digitalization and socioeconomic factors: education, wages, and gender.[33] The data used in this section maps data from the Burning Glass German database to data from the December 2018 European Labour Force Survey (LFS)[34] for Germany to understand the distribution across occupations of educational attainment, gender, and salary. These data can help shed light on the ways in which, without policy intervention, current trends of digitalization may be correlated with perpetuating inequality in the labor market. To use this data alongside the digitalization index, the occupations found in the LFS were mapped to the ESCO occupations. In order to match the German Classification of Occupations (KldB)[35] used by the LFS data to ESCO occupations used by Burning Glass data, a crosswalk was created based on a sample of postings. A complete methodology for developing this crosswalk can be found in Appendix I.

The data in this section is based on these reported survey results and is then matched to job postings data to assess the level of digitalization for each occupation. For education, the data is based on the reported education levels for employees in each occupation; for salary, the data is based on the reported monthly wages for employees in each occupation; and for gender, the data is based on the

Table 11: **Average Digital Index by Education Level[a]**

Education Level	Definition	Average Digital Index	Average Percent Employment Across all Occupations[b]
Academic Qualification	Including Bachelor, Diplom/Magister/Master/Staatsexamen, and Doctorate	62	21%
Recognized Professional Qualification	Including "with recognized vocational training" and "master craftsman/technician/equivalent technical college qualification"	51	57%
Without Vocational Training	No completed vocational training, (technical) university degree, or (technical) university entrance qualification (i.e. "(Fach)-Abitur")	50	11%

Source: Burning Glass Technologies

BertelsmannStiftung

a See, e.g., https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Bildungsstand/Publikationen/Downloads-Bildungsstand/bildung-deutschland-5210001189004.pdf?__blob=publicationFile for further description of education levels
b Approximately 9% of employees across all occupations do not report education levels.

32 Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. "Digitalization And The American Workforce." Brookings, November 2017. https://www.brookings.edu/wp-content/uploads/2017/11/mpp_2017nov15_digitalization_full_report.pdf
33 See Appendix I for a full description of the methodology used to assess these data.
34 "EU Labour Force Survey – Data and Publication - Statistics Explained." Accessed October 1, 2019. https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_labour_force_survey_%E2%80%93_data_and_publication
35 "KldB 2010 - Classification of Occupations, Issue 2010." Accessed October 1, 2019. https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=kldb2010&lang=EN

reported employee gender. Each section below shows the correlation between digitalization and these socioeconomic indicators. These analyses do not indicate the causal effect of digitalization but rather aim to show the correlation between digitalization and these factors.

Digitalization by Education

Table 11 shows the average digital index by education level. The highest average digital index occurs in occupations that require Academic Qualifications (62) while occupations that generally require a Recognized Professional Qualification or No Vocational Training have a comparable average

Table 12: **Education Distribution among Most Digital Occupations**

Occupation	Index	No Vocational Training	Recognized Professional Qualification	Academic Qualification	Unknown
Web and multimedia developers	100	10.8%	31.6%	**48.2%**	9.4%
Web technicians	98	7.3%	35.4%	**49.2%**	8.1%
Database designers and administrators	97	4.1%	34.1%	**54.2%**	7.6%
Systems administrators	96	4.7%	**62.2%**	28.4%	4.8%
Database and network professionals not elsewhere classified	95	5.4%	**49.5%**	38.5%	6.6%
Software developers	95	10.8%	36.8%	**45.1%**	7.4%
Computer network professionals	90	7.4%	**52.5%**	33.0%	7.1%
Applications programmers	89	8.9%	**41.8%**	40.8%	8.5%
Systems analysts	88	9.8%	38.3%	**44.9%**	7.0%
Software and applications developers and analysts not elsewhere classified	88	4.0%	38.6%	**50.7%**	6.8%
Most Digital Occupations Average	*94*	*7.3%*	*42.2%*	***43.3%***	*7.3%*

Source: Burning Glass Technologies

BertelsmannStiftung

Table 13: **Education Distribution Among Least Digital Occupations**

Occupation	Index	No Vocational Training	Recognized Professional Qualification	Academic Qualification	Unknown
Early childhood educators	19	7.9%	**79.6%**	9.4%	3.1%
Food and related products machine operators	19	22.5%	**52.4%**	3.0%	19.0%
Elementary workers not elsewhere classified	18	12.2%	**63.2%**	18.9%	5.7%
Kitchen helpers	18	24.2%	**48.7%**	3.2%	23.9%
Hairdressers	18	12.5%	**77.1%**	0.6%	9.8%
Cabinet-makers and related workers	17	10.0%	**61.5%**	3.3%	5.0%
Domestic housekeepers	13	15.7%	**69.1%**	4.6%	10.6%
Heavy truck and lorry drivers	11	10.2%	**68.6%**	1.0%	20.2%
Bricklayers and related workers	2	11.8%	**75.6%**	0.6%	12.0%
Cleaners and helpers in offices, hotels and other establishments	0	26.7%	**43.1%**	1.8%	28.3%
Least Digital Occupations Average	*14*	*15.4%*	***63.9%***	*4.7%*	*13.7%*

Source: Burning Glass Technologies

BertelsmannStiftung

digital index (51 and 50, respectively).

Tables 12 and 13 show the education distribution among the most digital occupations and the least digital occupations. Six of the 10 most digitally intensive occupations require primarily Academic Qualifications, while four require primarily Recognized Professional Qualifications. In all occupations, fewer than 12% of people employed report having no formal training. The average occupation employs 50% fewer people with an Academic Qualification than the most digital occupations (21.2% as compared to 43.3% respectively).

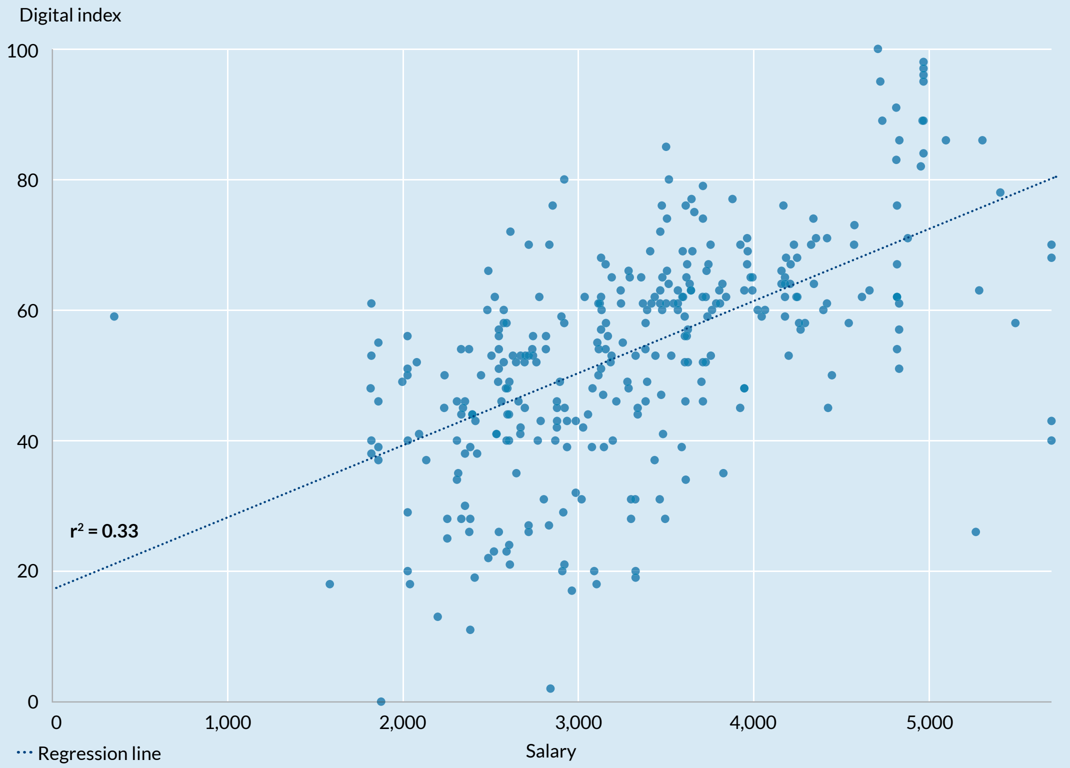
In contrast, the least digital occupations have much higher rates of employment of people with no training or with a Recognized Professional Qualification. On average, the least digital occupations employ 78% fewer people with an Academic Qualification than the average occupation (4.7% as compared to the average 21.2%) and 11% more people with a Recognized Professional Qualification (63.9% as compared to the average 56.6%).

These educational attainment differences indicate that digitalization is most intense in professions that currently largely require an Academic Qualification. While Recognized Professional Qualifications play a role in digital skills professions, they are more prevalent among the least digital occupations. Furthermore, occupations that primarily require Recognized Professional Qualifications have a comparable average digital score to occupations that primarily require no training. This implies more digital skill training should be included within Recognized Professional Qualification programs.

Digitalization by Salary

This section explores the relationship between digitalization and average monthly salary by occupation based on reported salaries from Labour Force Survey (LFS) data. It should be noted that the relationship between the digital index and salary is only correlational, and that factors such as educational attainment and industry will also affect salary.

Figure 9: **Digital Index vs. Average Monthly Salary**



Source: Burning Glass Technologies

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Table 14: **Average Monthly Salary of Most Digital Occupations**

Index	Occupation	Monthly Average Salary
100	Web and multimedia developers	€4,710
98	Web technicians	€4,970
97	Database designers and administrators	€4,970
96	Systems administrators	€4,970
95	Software developers	€4,724
95	Database and network professionals not elsewhere classified	€4,970
91	Computer network professionals	€4,814
89	Applications programmers	€4,735
89	Systems analysts	€4,964
89	Software and applications developers and analysts not elsewhere classified	€4,970
94	***Average Across Most Digital Occupations***	**€4,880**

Source: Burning Glass Technologies | BertelsmannStiftung

The digital index and average monthly salary across all occupations are positively correlated, with an r-squared of 0.33 as seen in Figure 9. Salaries in the middle of the range are widely spread across digitalization levels, whereas salaries at the high end of the range and the low end of the range are largely correlated with a high and low digital index, respectively. The average monthly salary for the least digital occupation is 60% lower than the average monthly salary for the most digital occupation.

Tables 14 and 15 emphasize this point: the average monthly salary of the most digital occupations is €4,880 which represents a salary premium of 48% above

Table 15: **Average Monthly Salary of Least Digital Occupations**

Index	Occupation	Monthly Average Salary
19	Early childhood educators	€3,328
19	Food and related products machine operators	€2,410
18	Elementary workers not elsewhere classified	€3,106
18	Hairdressers	€1,584
18	Kitchen helpers	€2,041
17	Cabinet-makers and related workers	€2,965
13	Domestic housekeepers	€2,199
11	Heavy truck and lorry drivers	€2,385
2	Bricklayers and related workers	€2,843
0	Cleaners and helpers in offices, hotels and other establishments	€1,877
14	***Average Across Least Digital Occupations***	**€2,474**

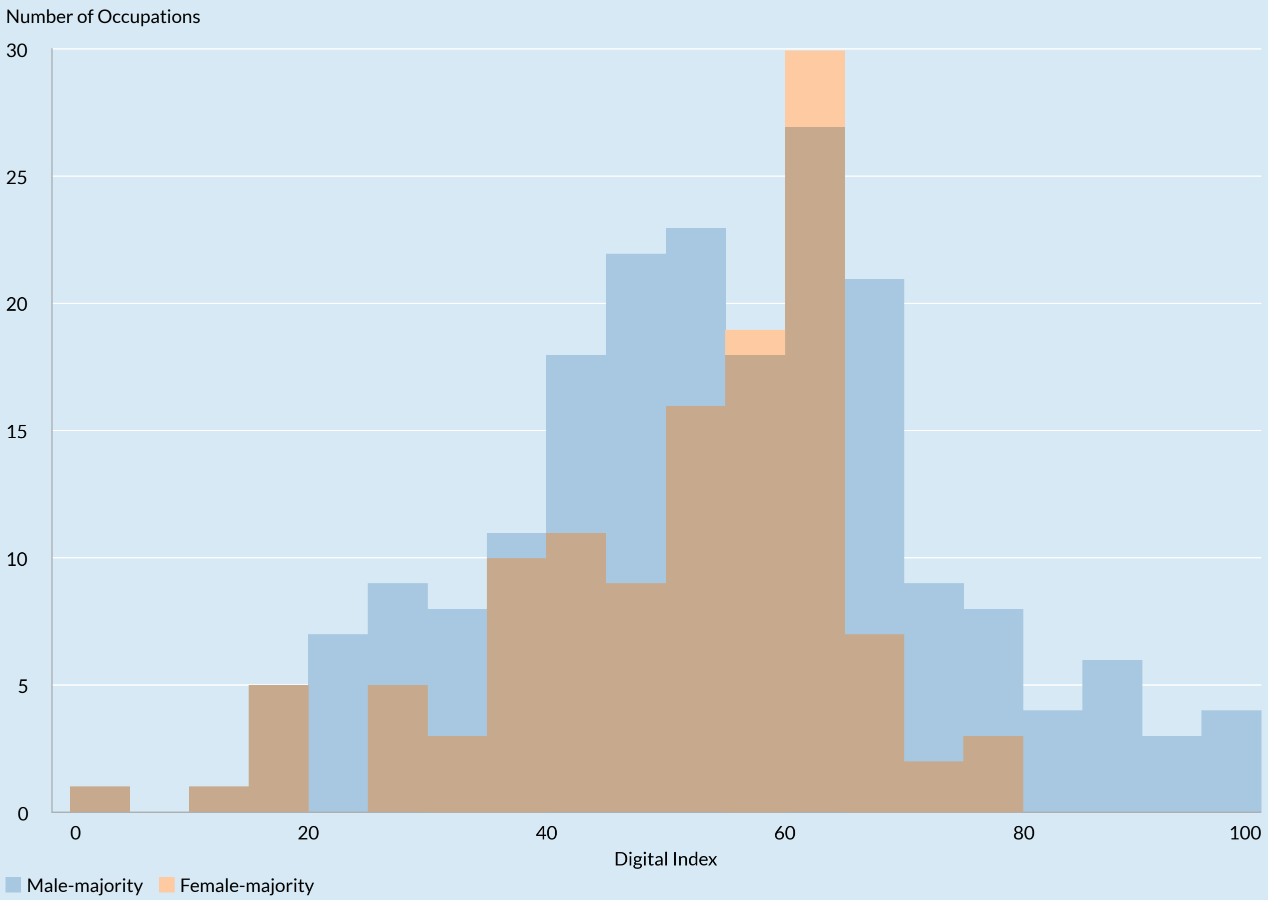
Source: Burning Glass Technologies | BertelsmannStiftung the average salary across all occupations, €3,302. In contrast, the average monthly salary of the least digital occupations is 26% below the average salary across all occupations. While the average monthly salaries of the most digital occupations are all above €4,500, the highest average monthly salary of the least digital occupations is €3,328, a difference of 35%.

Digitalization by Gender

The digital index can also provide insight into how digitalization differs across genders by assessing the difference in digitalization of male-majority and female-majority occupations. Occupations were determined to be male-majority or female-majority based on the reported gender of employees in each occupation in the European Labour Force Survey (LFS) for Germany. On average, the digital index by gender is comparable, at 47 for male-majority occupations and 44 for female-majority occupations. However, a closer look at the distribution of the index by gender reveals different trends for each occupation type.

Figure 10 details the distribution of the digital index for male-majority occupations and for female-majority occupations. The distribution of male-majority occupations is clearly wider, with substantially more occupations at the high end of the digital index; in fact, there are no female-majority occupations with a digital index above 80. The 90th percentile for male-majority occupations is an index of 77, whereas for female-majority occupations it is an index of 65, representing a large gender gap in digitalization. A closer look at the male-majority occupations with the highest indices in comparison to the female-majority

Figure 10: **Digital Index Distribution for Male- and Female-Majority Occupations**



Source: Burning Glass Technologies

BertelsmannStiftung

Table 16: **Top 10 Digital Indices for Male-Majority Occupations**

Occupation	% Male	% Female	Index	Index Rank
Web and multimedia developers	76.8	23.2	100	1
Web technicians	71.6	28.4	98	2
Database designers and administrators	74.8	25.2	97	3
Systems administrators	89.5	10.5	96	4
Database and network professionals not elsewhere classified	83.9	16.1	95	5
Software developers	84.6	15.4	95	5
Computer network professionals	87.5	12.5	91	7
Applications programmers	87.5	12.5	89	10
Systems analysts	81.9	18.1	89	10
Software and applications developers and analysts not elsewhere classified	76.7	23.3	89	10

Source: Burning Glass Technologies

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occupations with the highest indices is shown in Tables 16 and 17.

All 10 of the top most digital occupations are highly male-dominated. These jobs include developers, programmers, analysts, systems and database administrators, and network professionals and range in digital index from 88 to 100, representing the highest possible levels of digitalization. In contrast, the top 10 most digital occupations in female-majority jobs start at an index of 80, nine points below the lowest male-majority occupation. These jobs have a higher focus on design and creativity (Graphic and multimedia designers; Advertising and marketing professionals) and communications (Announcers on radio, television and other media; Public relations professionals; Conference and event planners; Authors and related writers). This also includes more medium- or low-skill jobs, including Typists and word processing operators, and Medical records and health information technicians as compared to the male-dominated jobs.

A notable difference in job characteristics is also clear at the other end of the distribution. Tables 18 and 19 show the least digital occupations for each male-

Table 17: **Top 10 Digital Indices for Female-Majority Occupations**

Occupation	% Male	% Female	Index
Graphic and multimedia designers	49.7	50.3	80
Advertising and marketing professionals	40.4	59.6	76
Announcers on radio, television and other media	49.6	50.4	76
Medical records and health information technicians	14.9	85.1	74
Public relations professionals	34.8	65.2	71
Conference and event planners	43.8	56.2	70
Authors and related writers	39.3	60.7	68
Typists and word processing operators	3.3	96.7	68
Accountants	44.7	55.3	67
Librarians and related information professionals	25.1	74.9	66

Source: Burning Glass Technologies

| BertelsmannStiftung

majority and female-majority occupations. The male majority occupations can be classified into two categories: construction and logistics occupations (Garden and horticultural labourers; Floor layers and tile setters; Welders and flamecutters; Spray painters and varnishers; Cabinet-makers and related workers; Heavy truck and lorry drivers; and Bricklayers and related workers), and food production occupations (Chefs; Food and related products machine operators; Kitchen helpers). In contrast, the female-majority occupations are largely service industry workers (Beauticians and related workers; Health care assistants; Hairdressers; and Domestic housekeepers) and child care workers and educators (Child care workers; Elementary workers not elsewhere classified; Early childhood educators). While these differences are consistent with occupational selection stories, they also illustrate the nuance with which policymakers will need to act in order to provide digital skills training that addresses these differences across gender.

Table 18: **Lowest 10 Digital Indices for Male-Majority Occupations**

Occupation	% Male	% Female	Index
Garden and horticultural labourers	79.7	20.3	22
Floor layers and tile setters	98.9	1.1	21
Spray painters and varnishers	92.1	7.9	21
Chefs	82.8	17.2	20
Welders and flamecutters	95.3	4.7	20
Food and related products machine operators	66.2	33.8	19
Kitchen helpers	50.2	49.8	18
Cabinet-makers and related workers	90.7	9.3	18
Heavy truck and lorry drivers	98.2	1.8	11
Bricklayers and related workers	71.3	28.8	2

Source: Burning Glass Technologies

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Table 19: **Lowest 10 Digital Indices for Female-Majority Occupations**

Occupation	% Male	% Female	Index
Shelf fillers	26.7	73.3	26
Beauticians and related workers	13.1	86.9	26
Specialist medical practitioners	39.5	60.5	26
Child care workers	10.5	89.5	20
Health care assistants	16.4	83.6	20
Early childhood educators	10.5	89.5	19
Hairdressers	12.8	87.2	18
Elementary workers not elsewhere classified	32.6	67.4	18
Domestic housekeepers	9.6	90.4	13
Cleaners and helpers in offices, hotels and other establishments	31.0	69.0	0

Source: Burning Glass Technologies

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Conclusions and Outlook

The analyses in this report have shown that workers in Germany are increasingly expected to have **digital skills**: since 2014, every occupation group (at ESCO Level 1) has increased in terms of digitalization, and occupations that were less digital in 2014 saw higher growth in digitalization. Demand for digital skills is also high across all qualification levels: the percentage of job posting requiring digital skills is 61.5% for low-skill occupations, 79.5% for middle-skill ones, and up to 94.4% for high-skill occupations. Basic digital skills, including using a computer and productivity software such as Microsoft Office, are the most highly requested skills in job vacancies, and are requested in one out of every five job postings in Germany. Regardless of occupation or skill level, most workers can benefit from acquiring digital skills, and the increased digitalization across occupations opens up additional career transition paths for those who learn these digital skills.

Digital intensity of demand varies across regions and industries. While many regions and specific areas show high digital intensity of demand, the nature of the digital skills required vary even within these places. Unsurprisingly, core German industries, such as Manufacturing, show high levels of digital intensity of demand. At the same time, other industries with high degrees of digitalization in other countries, such as Health Care in the US, still lag behind in terms of digital intensity in Germany.

Digitalization is correlated with various job characteristics. Analyzing the employment distribution by digitalization across educational attainment, wages, and gender reveals that digitalization often is correlated with these factors. The most highly digital occupations are heavily male-dominated. Average monthly salaries at the top of the digitalization distribution are at least 25% higher than the highest monthly salary at the bottom of the distribution. The more digitalized an occupation, the more frequently it requires an Academic Qualification rather than a Professional Qualification.

The insights acquired from these analyses give rise to a few areas for further action.

1. First, our findings suggest that digital skills are increasingly important for the vast majority of workers in the economy. Baseline digital skills, in particular, are highly demanded across occupations and have become even more so since 2014 – meaning they should be taught across a wide range of education levels, including in initial vocational training programs and lifelong learning programs. However, this is not necessarily the same case for more advanced and highly technical digital skills, such as computer programming or Java, which might better fit a specific section of workers in the economy. **Relevant actors should therefore understand which digital skills are most appropriately taught at each education level and focus their efforts accordingly**. Studies like ours can contribute to such a process.

2. Second, job postings can be a very useful tool to generate insights into the future demand for skills and can thus help make decisions regarding which skills are most worth investing in. **This information should be used in order to re-skill and up-skill workers and to thus ensure their long-term employability within a fast-changing economy impacted by digitalization and automation** – especially those at highest risk of losing their jobs. Without reskilling the workforce, businesses will be hard-pressed to hire those with the digital skills they will need, and workers will find themselves unable to keep up with changes in their jobs. The move toward

re- and up-skilling of the workforce should be supported by policymakers and businesses, so individuals can take the necessary steps to adapt and update their skills.

3. Third, businesses and social partners – including industry associations and trade unions – in Germany would benefit from understanding the specific digital skill gaps they face and the challenges associated with rapid digitalization in their industry. Job posting data can be one instrument to better understanding the specific challenges of a sector.

   In parallel, municipal governments could also benefit from understanding local digital skill requirements in order to develop and implement means to close digital skill gaps in tandem with industry. **Local and regional job postings data can be used to help governments and businesses understand these challenges in more detail.**

4. Finally, current trends suggest that digitalization and the demand for digital skills is most advanced in high-salary, highly educated, male-dominated occupations. It is therefore important to design efforts so as not to compound already existing wage and gender gaps. **Upskilling efforts in digital skills should not forget groups who could stand to benefit the most from increased digitalization, including women and those without academic qualifications.**

Appendix I: Data and Methods

Burning Glass German Data

Burning Glass' German online job posting database currently contains just over 22 million job postings in 2018 and just over 4 million job postings in 2014 (Table 20). Between 2014 and 2018, Burning Glass increased the number of sources from which job postings data was collected. The database tracks 3,111 distinct skills listed in job postings. These skills are broken down into the following skill types: Applied Management and Informatic Skills, Basic Information Skills, ICT Technical Skills, Information Brokerage Skills, and No Digital. Of the 3,111 distinct skills, 81% (2,528) of the skills are in the No Digital skill type (Table 21).

Table 20: **Number of job postings by year in Burning Glass data**

Year	2014	2018
Number of Posts	4,066,537	22,325,323

Source: Burning Glass Technologies | BertelsmannStiftung

Table 21: **Distinct Skills By Skill Type**

Skill Type	Number of Distinct Skills
No Digital	2,528
Basic Information Skills	25
Information Brokerage Skills	70
Applied & Management Informatic Skills	201
ICT Technical Skills	287

Source: Burning Glass Technologies | BertelsmannStiftung

Eurostat Comparison

The Eurostat Comparison section describes the distribution of occupations and industries available in the Burning Glass database and compares these distributions to public data from Eurostat on employment in Germany. The data in Eurostat represents the total stock of employees in each occupation, whereas the Burning Glass database represents expected flows into employment. In other words, Eurostat represents the distribution of total employment, while the Burning Glass database represents the distribution of job vacancies. As such, this comparison is meant to act as a guide to understanding how the Burning Glass database complements employment data, and the two distributions are not expected to be identical.

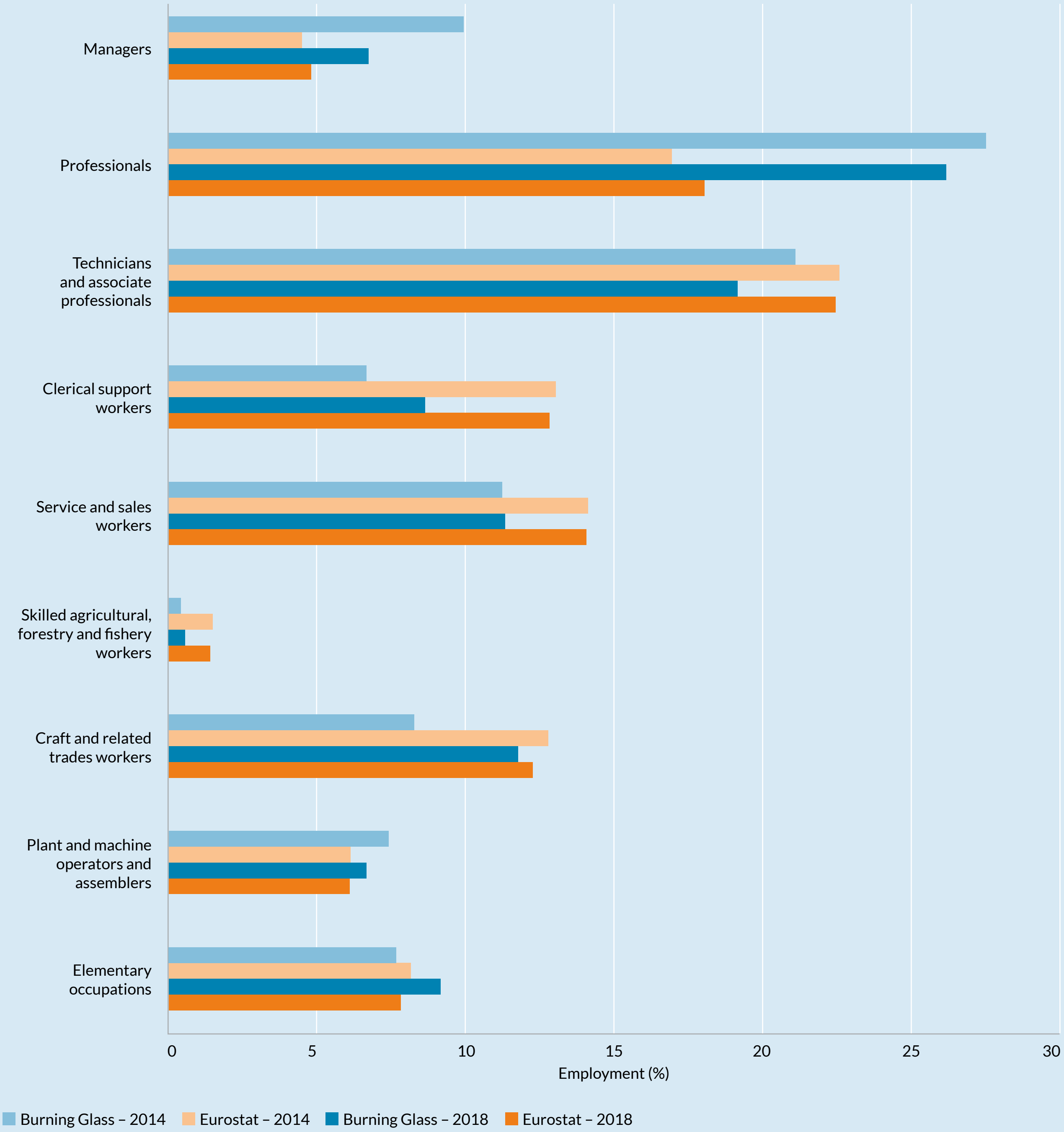
Comparison of Postings and Employment Distributions by Occupation (ESCO Level 1)

The distributions of occupations for Burning Glass and Eurostat are similar, with a Pearson correlation of .87 in 2018 and a Pearson correlation of .69 in 2014. The Professionals and Technicians and associate professionals occupations are the highest proportion of the database for both data sources, and Skilled agricultural, forestry and fishery workers is the lowest proportion in both.

Comparison of Posting and Vacancy Distributions by Industry (NACE 1)

The industry distributions are also highly correlated, with a Pearson correlation of .67 in 2018. The Technicians and associate professionals has the highest proportion of employment according to Eurostat data, while the Manufacturing industry is the highest proportion of Burning Glass postings data. Arts, entertainment, and recreation and Electricity, gas,

Figure 15: **Job Postings vs. Employment Distribution by Occupation**



Note: The two distributions are not expected to be identical since Eurostat represents the distribution of stock of employment across occupations, while Burning Glass data represents the distribution of job vacancies.

Source: Burning Glass Technologies

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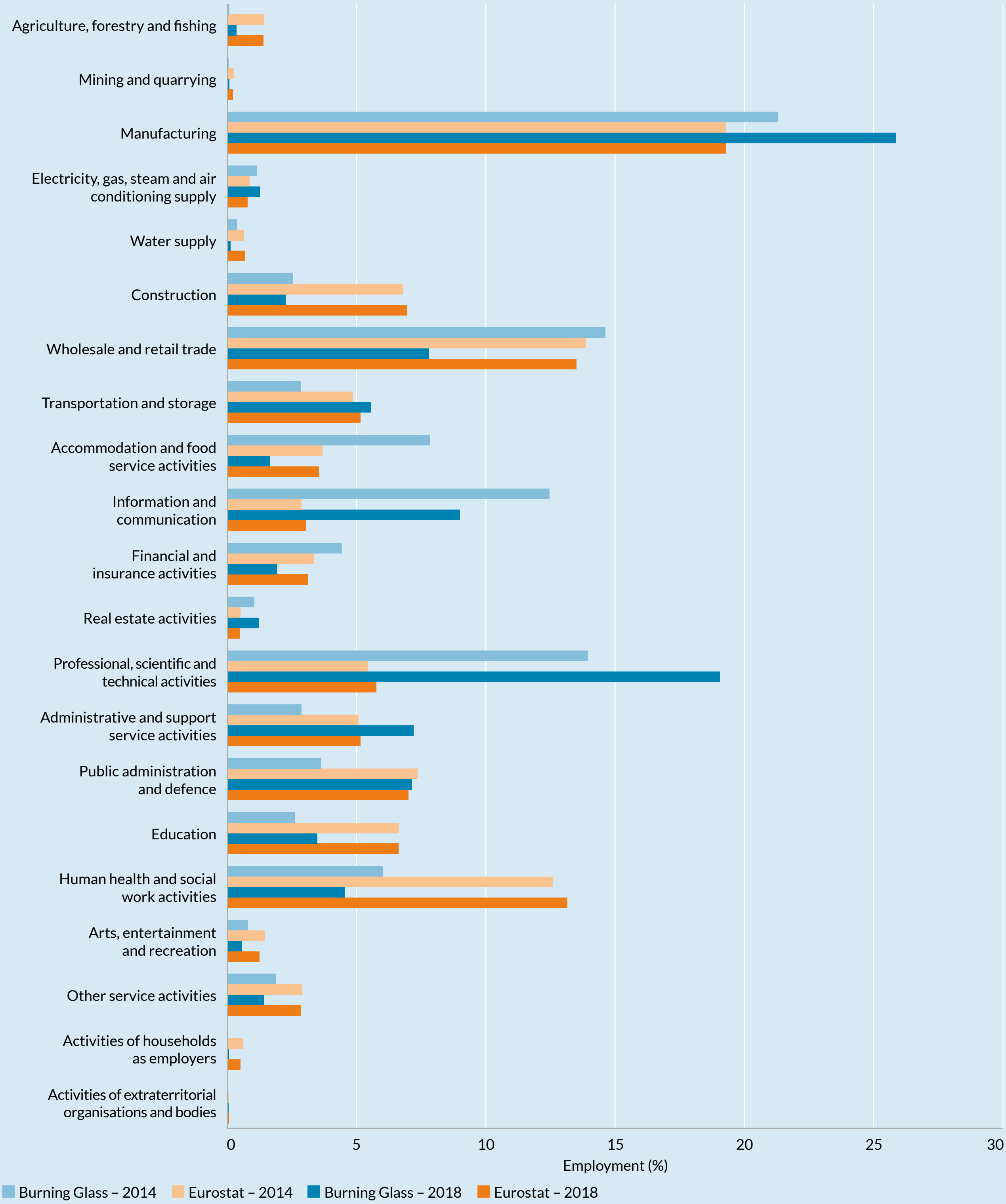
Figure 16: **Job Postings vs. Employment Distribution by Industry**



Note: The two distributions are not expected to be identical since Eurostat represents the distribution of stock of employment across occupations, while Burning Glass data represents the distribution of job vacancies.

Source: Burning Glass Technologies

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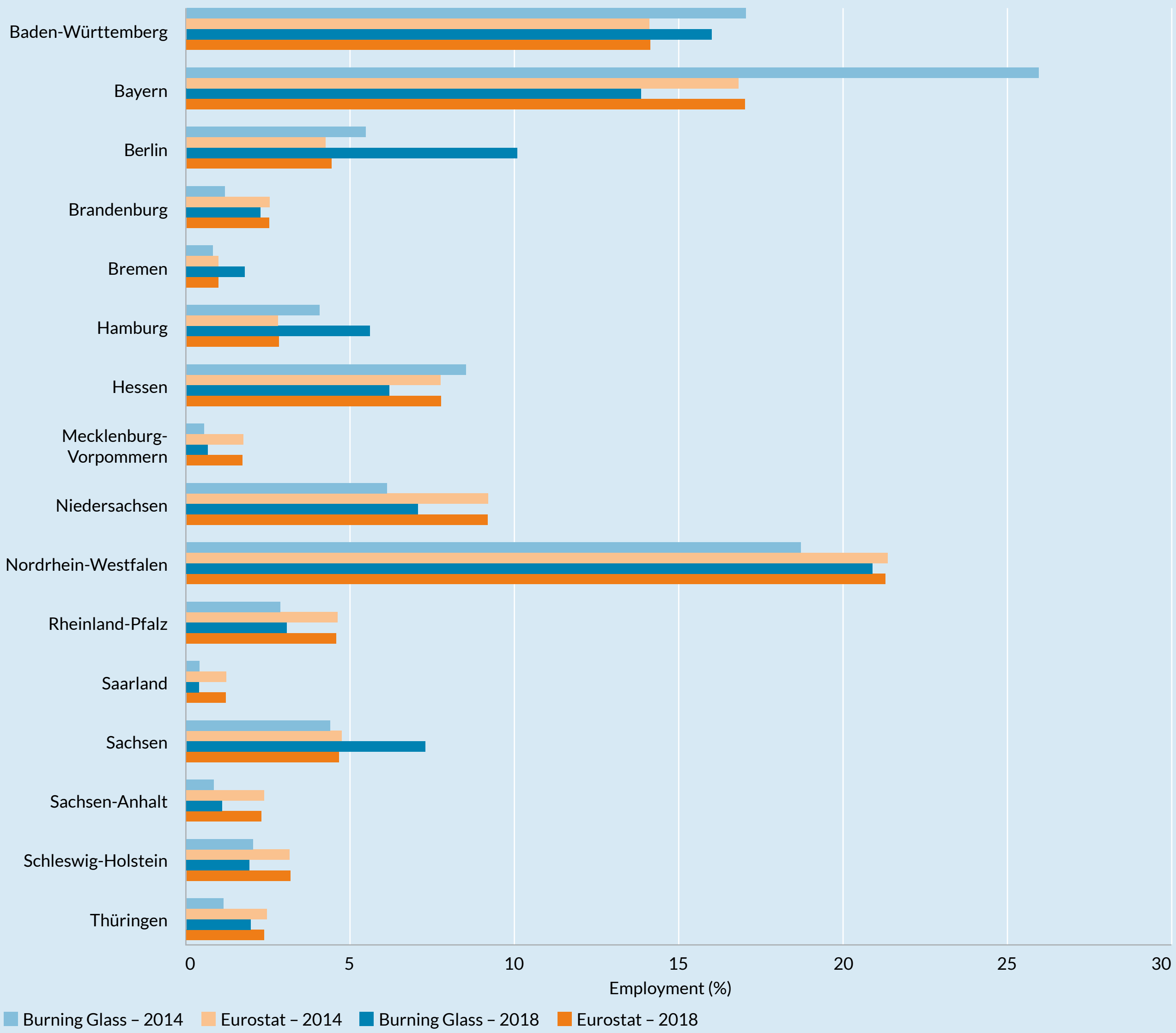
steam and air conditioning supply industries are the lowest proportion of data for both Eurostat and Burning Glass.

Comparison of Posting and Employment Distribution by Region (NUTS 1)

The Pearson correlations for regional online postings and employment is .93 in 2018 and .94 in 2014, which illustrates very high correlation. Bayern, Nordrhein-Westfalen and Baden-Württemberg comprise the highest distribution percentages, and Bremen the lowest.

Figure 17: **Job Postings vs. Employment by NUTS 1 Regions**



Note: The two distributions are not expected to be identical since Eurostat represents the distribution of stock of employment across occupations, while Burning Glass data represents the distribution of job vacancies.

Source: Burning Glass Technologies

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Index Methodology

Index Creation

The steps to create the index were as follows:

1. Compute the recall for each skill in each occupation

$$Recall_{o,s} = \frac{\text{\# of postings in O with skill S}}{\text{total \# of postings in occupation O}}$$

2. Multiply each recall by the weight of each skill's skill type, and sum by occupation (weights: [0; No Digital], [1, Basic Computer Skills], [1, Information Brokerage Skills], [1.5, Applied Management & Information Skills], [2, ICT Technical Skills])

$$Occupation_o = \sum_{S}^{Skills} Recall\_ij * Skill\ Type\ Weight\_W$$

3. As a first normalization step, take the log of each occupation value, which reduces the skewness of the distribution.

4. Normalize the occupation values to be between 0 and 100 based on the following formula, where O is Original score, H is highest score, and L is lowest score. This is done to allow for a more readily understandable score.

$$Norm = \frac{O-L}{H-L} *100$$

In order to ensure the chosen weights did not heavily influence the results, we ran sensitivity analyses by varying each weight value by up to 20% and assessing changes in the distribution of the digital index as a result. In no test did the top or bottom of the distribution of occupations by digital index change by more than 5%. The full results of these analyses are shown below in Table 22:

Table 22: **Percent Change in Digital Index Distribution**

Skill Type	Original Weight	Modified Weight	Top 20	Bottom 20	Top Third	Bottom Third
ICT Technical Skills	2	2.4	0.0%	0.0%	3.1%	1.5%
ICT Technical Skills	2	1.6	0.0%	0.0%	3.8%	0.8%
Applied & Management Information Skills	1.5	1.8	0.0%	0.0%	1.5%	0.8%
Applied & Management Information Skills	1.5	1.2	0.0%	5.0%	2.3%	0.0%
Information Brokerage Skills	1	1.2	0.0%	0.0%	1.5%	0.8%
Information Brokerage Skills	1	0.8	5.0%	0.0%	0.8%	0.0%
Basic Information Skills	1	1.2	5.0%	5.0%	2.3%	0.8%
Basic Information Skills	1	0.8	0.0%	0.0%	4.6%	2.3%

Source: Burning Glass Technologies

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German LFS Data and KldB Crosswalk Methodology

In order to match the German Classification of Occupations (KldB)[36] used by the LFS data to ESCO occupations used by Burning Glass data, a crosswalk was created based on title text similarity. The approach used has three steps:

1. Calculate the text similarity between KldB occupations and ESCO job descriptions by computing the frequency of each significant word in KldB occupation names that occur in ESCO job descriptions, ignoring common articles and pronouns such as "the", "in", and "and". For example, in comparing KldB occupation "senior tax accountant" and ESCO job description "Lead the tax accounting department, and proof end of year tax records" the frequency for all significant words would be: "senior" = 0, "tax" = 2, "accountant" = 0.

2. Compute the number of words that overlap based on the frequency analysis described in step 1 and calculate a normalized score by dividing the number of occurrences that overlap in each KldB-ESCO pair by the product of the number of relevant unique words in the KldB occupation name and the number of ESCO job descriptions where at least one occurrence of the words contained in the KldB job title has been found. The formula is as follows:

$$\text{Occupation score} = \frac{tf(x(i),k)}{len(j')*n}$$

- *j'*: preprocessed KldB job title (e.g. "managers technical media design" from "Managers in Technical Media Design")
- *x(i)* : relevant word *x* in position *i* in *j'*, where *i* in *{0, len(j')}* (e.g. *x0* is "managers")
- *tf(x(i),k)*: the number of times that term *x(i)* occurs in job description k, where k in *{0, p}* and p represents the total number of ESCO job descriptions
- n: number of job descriptions associated to title *j'* that contain at least one term from title *j'*. Thus, it follows that n ≤ p.

For example, given the following pairs and assuming these were the only pairs in the dataset:

KldB Occupation	ESCO Job Description
Managers in technical media design	Supervise **technical media design team**, and translate new **media** projects to partners in the organization.
Managers in technical media design	**Manage** the public image of the company. **Design** PR approaches for new products. Director level position.

The occupation score associated with the KldB occupation "Managers in technical media design" is computed as follows:

$$\text{Occupation score} = \frac{6}{4*2} = 0.75$$

Numerator: We obtained the following counts per word in the ESCO job descriptions: technical = 1, media = 2, design = 2, manage=1, which total to a sum of 6.

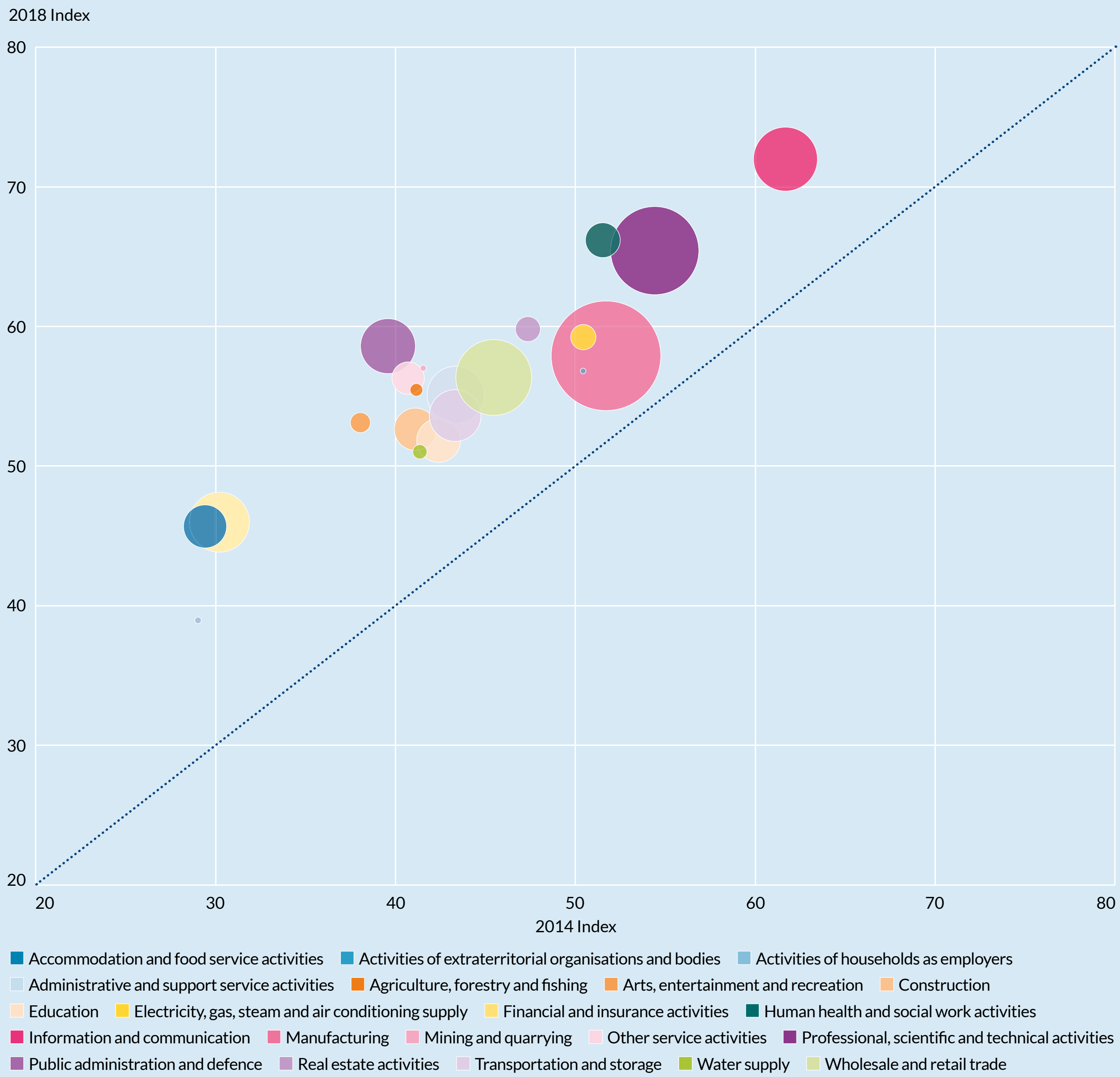
Denominator: The number of significant words in the KldB occupation is 4 ("manager", "technical", "media", and "design") and the number of ESCO job descriptions with at least one of those words is 2.

3. After calculating each occupation score, the scores per KldB occupation are normalized to sum to 1. Each normalized score is used as a weight to calculate ESCO occupation level variables.

36 "KldB 2010 - Classification of Occupations, Issue 2010." Accessed October 1, 2019. https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=kldb2010&lang=EN

Appendix II: Further Analyses

Figure 19: **2014 and 2018 Index by Industry**



Note: A bubble located above the dotted line indicates that the digitalization index for that industry has increased in 2018 in comparison to 2014. The size of the bubble corresponds to the demand (number of job postings) for occupations in that industry in 2018.

Source: Burning Glass Technologies

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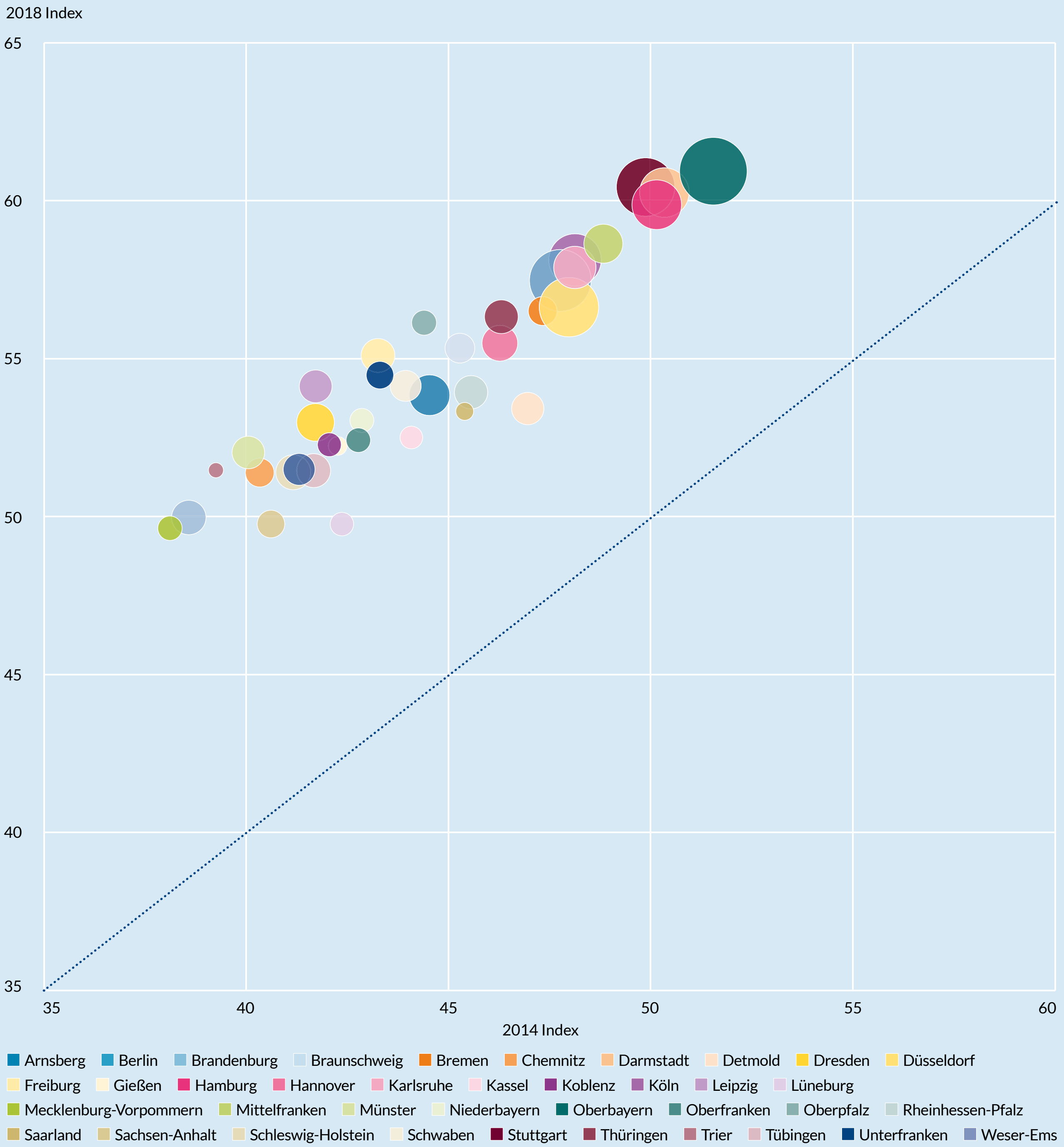
Figure 20: **2014 and 2018 Index by Region**



Note: A bubble located above the dotted line indicates that the digitalization index for that region has increased in 2018 in comparison to 2014. The size of the bubble corresponds to the demand (number of job postings) for occupations in that region in 2018.

Source: Burning Glass Technologies

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