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Final Thesis

# Analysis and classification of digital skills demanded in the job market

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# INTRODUCTION

Digitalization has had an enormous impact on the economy as a whole. Since it started decades ago, digitalization has unquestionably spurred economic development as well as altered industries, businesses, and consumption (Mentsiev et al., 2020). Of course, also the job market has been affected by it. The effects of digitalization on jobs have been described as both destructive and transformative (Fossen, Sorgner, 2019). Destructive effects are workers being replaced by machines, while transformative ones refer to occupations changing in terms of ways of performing tasks and productivity, as well as changes at wages level, with an increasing gap between high-skilled jobs and low-skilled ones (Kart, Adas, 2023).

Since digitalization is an ongoing process which is hard to conceptualize and measure (McKinsey, 2015; Calvino et al., 2018), it's important to find out the reverberations that this phenomenon has had so far on the job market. The aim of this thesis is in fact to investigate the job market by looking at the digital skills that today's occupations entail.
For this work is considered a "digital skill" the ability to adequately make use of a specific software. Therefore, only hard skills are taken into consideration, while soft skills are left out on purpose.

How this thesis examines the digital skills in the current job market is by implementing several different statistical analyses on data from the O*Net database, which is an online free database created with the sponsorship of the U.S. Department of Labor that contains updated information on professions. All professions are taken into consideration for this analysis for two distinct reasons; first, because a large share of jobs today require possessing some digital knowledge (Vasilescu et al., 2020); and second, because it is deemed to be more relevant to look at the whole job market rather than analyzing only few specific professions.
With this approach it is believed that it will be possible to have a better look on the digitalization level of all occupations and also to see what jobs are similar on the basis of

digital skills required. It is important to highlight though that this work is based on a U.S. database and therefore all the information stored in there refers to the American job market. Therefore, the results of this thesis will be extremely indicative for the U.S. as well as for comparable economies, but it might be less indicative for very diverse ones.

Another reason supporting the choice of this topic as the subject for the thesis is the lack of research on it. As a matter of fact, most of the research papers that study the effects of digitalization on the job market either examine them at an aggregate level, by looking at the social and economic consequences (Blix, 2017; Fossen and Sorgner, 2019; Fossen and Sorgner, 2022; Kart and Adas, 2023), or focus on single occupations (Reyes-de-Cozar et al., 2022; Rosas Quintero, 2022; Suarta et al., 2023).

There are some studies that investigate the digital skills entailed by all jobs and that have an analytical approach. For example, Cirillo et al. (2020) looked at the INAPP-ISTAT Survey on Italian Occupations (ICP) to find out the levels of digitalization of occupations, but they only used as indices to measures them the use of computers and e-mails on the workplace. Colombo et al. (2019) calculated different skills required by the job market using web vacancies to construct a taxonomy for them. They distinguished between digital skills and non-digital skills, but they did not examine the latter in depth as they only split them into four different sub-groups.

The paper that this thesis is most akin to in terms of both content and analytical approach is Lennon et al. (2023). The authors in this study measured the digital skills requirements of occupations through the development of an indicator based on data gathered from the European Skills, Competences, and Occupations database (ESCO). Albeit this work is similar to the thesis as for the granularity of the data it uses, it differs for the fact that all the data is not directly available in the database but is rather collected using a text mining technique. Thus, those digital skills the authors examined had to be identified first by themselves using subjective parameters, while in the thesis the digital skills analyzed are already given.

## STRUCTURE OF THE THESIS AND METHODOLOGY

The thesis is divided into three chapters. The first one introduces the O*Net database, explaining how it's structured, what other piece of information it contains, as well as how it gathers all the data. In chapter two there's the part of descriptive analysis, where the frequencies of digital skills and the classification of jobs by number of skills are computed. The third and last chapter contains three different cluster analyses that investigate the relationships among occupations as well as how similar they are in terms of digital skills required. Moreover, chapter three includes a predictive algorithm that is meant to classify a given set of digital skills into one of the clusters created.

For the calculations needed for this thesis, different algorithms were used. As for the software employed, both Stata and RStudio were utilized, with Stata being used for the descriptive analyses and RStudio for the clustering part.

# CHAPTER 1: The O*Net database

## 1.1 Taxonomy structure and Content Model

This thesis is based on several statistical analyses of data that comes from the O*Net database, which is a free online database containing information on jobs. O*Net is the shortened form for "Occupational Information Network".

The O*Net Program is a project started in the 1990s under the sponsorship of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA) through a grant to the North Carolina Department of Commerce. O*Net replaced the Dictionary of Occupational Title (DOT), which was a publication produced periodically by the United States Department of Labor (DOL) from 1939 through 1999 that included several thousand definitions of jobs (Dictionary of Occupational Titles Introduction, https://occupationalinfo.org/front_148.html).

The O*Net database contains 1.016 occupations; 923 of them are defined "data-level occupations", that are those occupations for which a job description as well as much more information is provided. The 93 remaining "non-data level occupations" are, on the other hand, those occupations whose only information given in the database is the job title (Christina Gregory et al., 2019).

The current O*Net taxonomy structure is based on the 2018 Standard Occupational Classification (SOC) system, which is a statistical standard used by US federal agencies to classify workers into occupational categories. This system consists of classifying workers into one of 867 detailed occupations according to their occupational definition. In order to facilitate classification, detailed occupations are in turn combined to form 459 broad occupations, 98 minor groups, and 23 major groups on the basis of similar job duties, skills, education, and training. All SOC occupations are assigned a six-digit code as in the following example:

*13-1082 Project Management Specialist*

The first and second digits represent the major group; the fourth and the fifth digits represent the broad occupation; and the sixth digit represent the detailed occupation.
O*Net in some cases describes occupations at a more detailed level than does the SOC to reflect needed occupational specificity, thus identifying 149 more jobs and reaching the total number of 1.016 occupations. Therefore, the O*Net taxonomy, formally called O*Net-SOC Taxonomy, adds a two-digit extension to the six-digit SOC code, as in the example:

*15-1299.08 Computer Systems Engineers/Architects*

If the occupation title and definition are directly adopted from the SOC system, then the two-digit extension will be 00. In cases where the O*Net-SOC occupation is more detailed than the original SOC detailed occupation, the two-digit extension will be higher than 00, starting from 01 and up to as many detailed O*NET-SOC occupations are linked to the particular SOC detailed occupation (Gregory et al., 2019).

The information provided by O*Net is systematically organized following a conceptual framework called "O*Net Content Model". This framework consists of categorizing that information into six major domains: three of them are job-oriented, meaning they focus on what the specific job entails in terms of tasks, work context, tools to use, technology skills, as well as occupational statistics and projections for the specific occupation; the other three groups are worker-oriented and they include information about the skills, experience, and qualities a person needs to have in order to be selected for that position and how much they are related to performance in the specific job.
The six domains in which O*Net classifies its knowledge are:

- Occupation-specific information
- Workforce characteristics
- Occupational requirements
- Experience requirements

- Worker requirements
- Worker characteristics

Occupation-specific information, workforce characteristics, and occupational requirements are the job-oriented domains; experience requirements, worker requirements, and worker characteristics are worker-oriented groups.

## 1.2 Technology Skills database

The statistical analysis part of this thesis was implementing using data from the "Technology Skills" file of the O*Net database. This file displays jobs and all the digital skills that can be required for each occupation. The database is made up of seven columns and 32.385 rows.

| O*NET-SOC Code | Title | Example | Commodity Code | Commodity Title | Hot Technology | In Demand |
|---|---|---|---|---|---|---|
| 11-3021.00 | Computer and Information Systems Managers | Microsoft FrontPage | 43232107 | Web page creation and editing software | N | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Internet Explorer | 43232705 | Internet browser software | N | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Office SharePoint Server MOSS | 43233503 | Network conferencing software | N | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Office software | 43231513 | Office suite software | Y | Y |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Outlook | 43233501 | Electronic mail software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft PowerPoint | 43232106 | Presentation software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Project | 43231507 | Project management software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft SharePoint | 43233513 | Cloud-based data access and sharing software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft SQL Server | 43232306 | Data base user interface and query software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft SQL Server Reporting Services SSRS | 43232405 | Object or component oriented development software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Visio | 43231518 | Process mapping and design software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Visual Basic | 43232402 | Development environment software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Visual Basic Scripting Edition VBScript | 43232402 | Development environment software | N | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Visual FoxPro | 43232311 | Object oriented data base management software | N | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Visual Studio | 43232402 | Development environment software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Windows Server | 43232701 | Application server software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Microsoft Word | 43232104 | Word processing software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | MicroStrategy | 43232314 | Business intelligence and data analysis software | Y | N |
| 11-3021.00 | Computer and Information Systems Managers | Mobile wireless network infrastructure software | 43232910 | Wireless software | N | N |

*Figure 1 Screenshot from Technology Skills file.*

As can be seen in figure 1, each column represents a different piece of information.

Starting from the left, in the first column there is the O*Net-SOC code, which is the identification number each job possesses. The second column is named “Title” and contains the job titles corresponding to the O*Net-SOC code.

The third and the fifth column are strictly connected to each other. The “Example” column lists specific digital skills associated with O*Net-SOC occupations. The column “Commodity Title” classifies the examples under the United Nations Standard Products and Services Codes (UNSPSC) taxonomy; related to that is the “Commodity Code” column, which includes the identifying codes associated with their respective UNSPSC commodities. Since the UNSPSC classification gives a broad description of digital skills, it can happen that the same job is associated with the same commodity title twice or more. For example, “Administrative Services Managers” have among others as digital skills under the “Example” column: “Fund accounting software”, “Intuit Quickbooks”, and “Sage 50 Accounting”; all of the three are classified according to the UNSPSC taxonomy as “accounting software”.

The last two columns are, in order from left to right, “Hot Technology” and “In Demand”. Each value in both columns can be either “Y”, which stands for “yes”, or “N”, that stands for “no”. The hot technology column indicates whether a digital skill is frequently required by employers in different jobs. The in-demand column specifies if a technology skill is a requirement often included in job postings for that particular occupation. Although related, these classifications do not imply that if a skill is indicated as a hot technology, then it must also be in demand and the other way around (Lewis Morris, 2022).

## 1.3 Data collection

O*Net uses a multiple-method approach to collect data, in order to maximize the information for each occupation, while minimizing data collection costs (Supporting statement for O*Net data collection program, 2023).

The main method used entails implementing a survey of establishment, which is a kind of survey aims to measure the behavior, structure, or output of organizations rather than individuals.

The survey process starts with the selection of certain businesses. Consequently, some workers from those same businesses are sampled and asked to fill in a questionnaire. This method is called "The Establishment Method" and it is O*Net's preferred source of data for most domains of information.

Even though surveying job incumbents is considered to be the most effective data collection method, in some cases a second procedure called "Occupation Expert Method" is used. This method consists of sampling people who are specialists in a certain job, rather than job incumbents.
Are considered experts regarding an occupation supervisors, trainers, and experienced job incumbents. More in the details, someone in order to be considered an occupation expert must have worked in the position for at least 1 year and has 5 years of experience as an incumbent, trainer, or supervisor. Moreover, an occupation expert must have had experience with the occupation within the most recent 6 months.
There can be multiple reasons behind the choice of using this mechanism instead of the Establishment Method. These reasons can be: job incumbents' population is too small; surveying incumbents who are in remote locations that are difficult to access; the occupation is new and emerging and thus there are not many job incumbents available; as well as any other general case for which the Establishment Method is considered to be inefficient or ineffective.

Both job incumbents and occupation experts are asked to complete the same questionnaires. There are in total three different questionnaires, each one representing a single domain: Knowledge, Generalized Work Activities, and Work Context. Job incumbents are asked to fill in only one of three questionnaires randomly selected, while experts are asked to complete all three of them. Both categories are also requested to provide basic demographic information and to complete a brief task inventory.

A third source of information for the O*Net database is occupational analysts (Fleisher Tsacoumis, 2012).

Occupational analysts are job experts who are selected by the O*Net Program as they possess all the following characteristics:

- Have at least two years of work experience in any field; it can be either full time or part time work, while internships, summer jobs, and research assistantships positions in school don't count.

- Have completed two years of graduate school in either Industrial/Organizational Psychology, Vocational Psychology, Human Resources, or Industrial Relations.

- Have completed courses in both job analysis (or something comparable) and research methods (or something comparable).

The work experience requirement is set to ensure that the analysts are highly familiar with a job environment and job responsibilities. The education and course requirements are set to ensure that the occupational analysts have training and experience working with job analytical terminology as well as constructs and measurement methodology.

Before starting with their analysis, they are also asked to attend an 8-hour long training session and to read a manual provided by O*Net staff, so that their contribution is valid and reliable.

Occupational analysts contribute to O*Net database by assessing importance and required level of skills and abilities for all occupations listed in the database.

Occupational analysts are also in charge of identifying technology skills and tools linked to each job. To do so, they use data mining software to gather data from multiple online sources. These sources can be: occupation information systems, career information systems, job postings, vocational information websites, professional association websites, competency listings, and education/training curricula.

After they've collected all possible data, they review and process it. Eventually, they proceed to link each tool and technology to its corresponding code according to the UNSPSC classification. In this last part, when either tools or computer software are hard to classify, analysts can be helped by IT experts in the process.

The same software and procedure are used by analysts to identify digital skills that are considered “hot technologies” and/or “in demand” and that can be found in the Technology Skills database

# CHAPTER 2: Descriptive analysis

The first analytical part of this thesis consists of five different descriptive analyses of the most relevant categories that make up the Technology Skills file.
In order to carry out these analyses, the software Stata was employed. Of that software, the only command that was used was the one-way frequency table, as it was the only one needed for the kind of information of interest.
For this part, the whole tables containing all the results are not included in the thesis as they are too long, and they'd take up too much space. Instead, they are replaced with smaller tables that include the most important outcomes.
The whole tables are available for being examined in the files attached to the thesis.

## 2.1 Digital skills frequency

### *2.1.1 Frequency of generic digital skills*

The very first computing consisted of calculating the frequency of each UNSPSC commodity title present in the file and arrange the results into a table. In here are reported only the most frequent generic skills that all together represent 90% of the total observations.

| Commodity Title | Frequency | Percentage | Cumulative |
|---|---|---|---|
| Analytical or scientific software | 2860 | 8,83% | 8,83 |
| Data base user interface and query software | 2488 | 7,68% | 16,51 |
| Medical software | 1608 | 4,97% | 21,48 |
| Word processing software | 1398 | 4,32% | 25,80 |
| Enterprise resource planning ERP software | 1251 | 3,86% | 29,66 |
| Development environment software | 1160 | 3,58% | 33,24 |
| Electronic mail software | 1122 | 3,46% | 36,71 |
| Computer aided design CAD software | 1062 | 3,28% | 39,99 |
| Spreadsheet software | 1053 | 3,25% | 43,24 |

| | | | |
|---|---|---|---|
| Operating system software | 986 | 3,04% | 46,28 |
| Office suite software | 913 | 2,82% | 49,10 |
| Object or component oriented development software | 880 | 2,72% | 51,82 |
| Graphics or photo imaging software | 850 | 2,62% | 54,44 |
| Web platform development software | 835 | 2,58% | 57,02 |
| Presentation software | 770 | 2,38% | 59,40 |
| Project management software | 689 | 2,13% | 61,53 |
| Financial analysis software | 601 | 1,86% | 63,38 |
| Internet browser software | 557 | 1,72% | 65,10 |
| Data base management system software | 550 | 1,70% | 66,80 |
| Computer based training software | 515 | 1,59% | 68,39 |
| Accounting software | 502 | 1,55% | 69,94 |
| Document management software | 436 | 1,35% | 71,29 |
| Web page creation and editing software | 434 | 1,34% | 72,63 |
| Customer relationship management CRM software | 409 | 1,26% | 73,89 |
| Human resources software | 393 | 1,21% | 75,10 |
| Video creation and editing software | 379 | 1,17% | 76,28 |
| Geographic information system | 348 | 1,07% | 77,35 |
| Business intelligence and data analysis software | 319 | 0,99% | 78,33 |
| Industrial control software | 317 | 0,98% | 79,31 |
| Desktop publishing software | 302 | 0,93% | 80,25 |
| Information retrieval or search software | 300 | 0,93% | 81,17 |
| Cloud-based data access and sharing software | 291 | 0,90% | 82,07 |
| Calendar and scheduling software | 280 | 0,86% | 82,94 |
| Enterprise application integration software | 240 | 0,74% | 83,68 |
| Program testing software | 230 | 0,71% | 84,39 |
| Map creation software | 225 | 0,69% | 85,08 |
| Materials requirements planning logistics and supply chain software | 220 | 0,68% | 85,76 |
| Computer aided manufacturing CAM software | 219 | 0,68% | 86,44 |
| Point of sale POS software | 207 | 0,64% | 87,08 |
| Inventory management software | 203 | 0,63% | 87,70 |
| Application server software | 193 | 0,60% | 88,30 |
| Video conferencing software | 180 | 0,56% | 88,86 |
| Network monitoring software | 171 | 0,53% | 89,38 |
| Data base reporting software | 168 | 0,52% | 89,90 |
| Configuration management software | 166 | 0,51% | 90,42 |

*Table 1 Commodity title frequency table. Source: personal elaboration*

In total there are 135 different generic skills and 32.384 observations. In Table 1 there are listed 45 of those skills and 30.506 observations.

By looking at the original table, one can see that almost all commodity skills can be divided into two main groups.

The first group comprehends those generic skills that are specific to occupations which are similar in terms of industry they're part of, knowledge required, tasks carried out, and educational background. This is the case among others of the following skills: "analytical or scientific software" (2.860 observations), "medical software" (1.608 observations), "enterprise resource planning ERP software" (1.251 observations), "development environment software" (1.160 observations), and "computer aided design CAD software" (1.062 observations).

The other main group includes skills that are generally used by the vast majority of occupations. Examples of these commodity with the highest frequency are: "data base user interface and query software" (2.488 observations), "word processing software" (1.398 observations), "electronic mail software" (1.122 observations), "spreadsheet software" (1.053 observations), and "operating system software" (986 observations).

### *2.1.2 Frequency of specific digital skills*

After calculating the frequency of the generic digital skills, the second step of the analysis consisted of computing the frequency of the specific ones, which are found in the database in the example column.

Given that there are way more specific digital skills than generic ones, this other table includes way fewer skills in terms of percentage of observations on total. As a result, here's copied a small fraction of the original table that contains those specific digital skills that all together make up the 40% of total observations.

| Example | Frequency | Percentage | Cumulative |
|---|---|---|---|
| Microsoft Excel | 855 | 3,05% | 2,64 |
| Microsoft Office software | 806 | 2,88% | 5,13 |
| Microsoft Word | 783 | 2,80% | 7,55 |
| Microsoft PowerPoint | 626 | 2,23% | 9,48 |
| Microsoft Outlook | 624 | 2,23% | 11,41 |
| Web browser software | 430 | 1,54% | 12,73 |
| Microsoft Access | 369 | 1,32% | 13,87 |

| | | | |
|---|---|---|---|
| Word processing software | 297 | 1,06% | 14,79 |
| SAP software | 279 | 0,99% | 15,65 |
| Email software | 276 | 0,98% | 16,51 |
| Microsoft Windows | 234 | 0,83% | 17,23 |
| Microsoft Project | 201 | 0,72% | 17,85 |
| Autodesk AutoCAD | 171 | 0,61% | 18,38 |
| Database software | 166 | 0,59% | 18,89 |
| Microsoft SharePoint | 165 | 0,59% | 19,40 |
| Adobe Systems Adobe Acrobat | 165 | 0,59% | 19,91 |
| Structured query language SQL | 150 | 0,53% | 20,37 |
| Microsoft Visio | 149 | 0,53% | 20,83 |
| Adobe Systems Adobe Photoshop | 145 | 0,52% | 21,28 |
| Spreadsheet software | 140 | 0,50% | 21,71 |
| Facebook | 134 | 0,47% | 22,13 |
| Python | 123 | 0,44% | 22,50 |
| Linux | 121 | 0,43% | 22,88 |
| SAS | 118 | 0,42% | 23,24 |
| Microsoft Dynamics | 118 | 0,42% | 23,61 |
| C++ | 110 | 0,39% | 23,95 |
| The MathWorks MATLAB | 109 | 0,39% | 24,28 |
| Google Docs | 106 | 0,38% | 24,61 |
| IBM Notes | 104 | 0,37% | 24,93 |
| Adobe Systems Adobe Illustrator | 99 | 0,36% | 25,24 |
| Oracle Java | 98 | 0,35% | 25,54 |
| Microsoft Visual Basic | 96 | 0,35% | 25,84 |
| Microsoft SQL Server | 95 | 0,34% | 26,13 |
| FileMaker Pro | 95 | 0,34% | 26,42 |
| Microsoft Publisher | 94 | 0,34% | 26,71 |
| IBM SPSS Statistics | 92 | 0,32% | 27,00 |
| ESRI ArcGIS software | 92 | 0,32% | 27,28 |
| R | 91 | 0,32% | 27,56 |
| UNIX | 88 | 0,31% | 27,83 |
| Oracle Database | 87 | 0,31% | 28,10 |
| Extensible markup language XML | 87 | 0,31% | 28,37 |
| Adobe Systems Adobe InDesign | 86 | 0,31% | 28,64 |
| JavaScript | 84 | 0,30% | 28,90 |
| Intuit QuickBooks | 83 | 0,30% | 29,15 |
| Salesforce software | 82 | 0,29% | 29,41 |
| Oracle PeopleSoft | 79 | 0,28% | 29,65 |
| Hypertext markup language HTML | 78 | 0,28% | 29,89 |
| MEDITECH software | 77 | 0,28% | 30,13 |
| YouTube | 74 | 0,27% | 30,36 |
| Enterprise resource planning ERP software | 73 | 0,27% | 30,58 |
| Geographic information system GIS software | 71 | 0,25% | 30,80 |
| Tableau | 70 | 0,25% | 31,02 |

| | | | |
|---|---|---|---|
| Scheduling software | 70 | 0,25% | 31,23 |
| Minitab | 70 | 0,25% | 31,45 |
| Oracle JD Edwards EnterpriseOne | 69 | 0,24% | 31,66 |
| Operating system software | 67 | 0,24% | 31,87 |
| Perl | 66 | 0,23% | 32,07 |
| Computer aided design CAD software | 66 | 0,23% | 32,28 |
| C | 65 | 0,23% | 32,48 |
| Google Drive | 64 | 0,23% | 32,68 |
| Corel WordPerfect Office Suite | 63 | 0,22% | 32,87 |
| Supervisory control and data acquisition SCADA software | 62 | 0,22% | 33,06 |
| National Instruments LabVIEW | 62 | 0,22% | 33,25 |
| Microsoft Internet Explorer | 61 | 0,22% | 33,44 |
| Dassault Systemes CATIA | 60 | 0,22% | 33,63 |
| Microsoft Exchange | 59 | 0,21% | 33,81 |
| Adobe Systems Adobe Dreamweaver | 59 | 0,21% | 33,99 |
| Dassault Systemes SolidWorks | 58 | 0,21% | 34,17 |
| Oracle Primavera Enterprise Project Portfolio Management | 57 | 0,21% | 34,35 |
| LexisNexis | 57 | 0,21% | 34,52 |
| Blackboard software | 57 | 0,21% | 34,70 |
| Apple macOS | 57 | 0,21% | 34,88 |
| Epic Systems | 56 | 0,20% | 35,05 |
| C# | 55 | 0,20% | 35,22 |
| StataCorp Stata | 54 | 0,20% | 35,38 |
| Teradata Database | 53 | 0,18% | 35,55 |
| LinkedIn | 53 | 0,18% | 35,71 |
| IBM Cognos Impromptu | 53 | 0,18% | 35,88 |
| Graphics software | 52 | 0,18% | 36,04 |
| Atlassian JIRA | 52 | 0,18% | 36,20 |
| SAP Business Objects | 51 | 0,18% | 36,35 |
| Oracle Hyperion | 51 | 0,18% | 36,51 |
| Geographic information system GIS systems | 50 | 0,17% | 36,67 |
| Qlik Tech QlikView | 49 | 0,17% | 36,82 |
| MySQL | 49 | 0,17% | 36,97 |
| Microsoft Dynamics GP | 49 | 0,17% | 37,12 |
| Microsoft Active Server Pages ASP | 49 | 0,17% | 37,27 |
| NetSuite ERP | 48 | 0,17% | 37,42 |
| PHP | 47 | 0,17% | 37,56 |
| Microsoft Visual Studio | 47 | 0,17% | 37,71 |
| Learning management system LMS | 47 | 0,17% | 37,86 |
| eClinicalWorks EHR software | 47 | 0,17% | 38,00 |
| Calendar and scheduling software | 47 | 0,17% | 38,15 |
| Amazon Web Services AWS software | 47 | 0,17% | 38,29 |
| MicroStrategy | 46 | 0,16% | 38,43 |
| Microsoft Azure software | 46 | 0,16% | 38,57 |
| Git | 46 | 0,16% | 38,72 |

| | | | |
|---|---|---|---|
| Bentley MicroStation | 46 | 0,16% | 38,86 |
| Adobe Systems Adobe Creative Cloud software | 46 | 0,16% | 39,00 |
| Oracle Business Intelligence Enterprise Edition | 45 | 0,16% | 39,14 |
| Oracle E-Business Suite Financials | 45 | 0,16% | 39,28 |
| Microsoft Visual Basic for Applications VBA | 45 | 0,16% | 39,42 |
| Medical procedure coding software | 45 | 0,16% | 39,56 |
| Inventory tracking software | 45 | 0,16% | 39,70 |
| Apple Final Cut Pro | 45 | 0,16% | 39,83 |
| SmugMug Flickr | 44 | 0,16% | 39,97 |
| SAP Crystal Reports | 44 | 0,16% | 40,11 |

*Table 2 Example frequency table. Source: personal elaboration*

By looking at the original table, what strikes the most is the fact that the majority of digital skills there have very few observations each. As a matter of fact, there are 7.517 specific digital skills that only have maximum two observations each, which implies that 7.517 skills are specific to either one or two for profession. This means that most of these competencies are extremely specific to very few jobs and that the O*Net database is truly detailed for what concerns digital skills in the job market, which makes it a very important indicator of current digitalization level of occupations.

Another difference between this second table and the first one is that the most frequent specific skills are all common to most occupations and are not specific to a certain industry or to professions that are similar in terms of knowledge, tasks, or educational background. This can be seen in the top ten frequent skills, where "Microsoft Excel" (855 observations), "Microsoft Office Software" (806 observations), "Microsoft Word" (783 observations), "Microsoft PowerPoint" (626 observations), "Microsoft Outlook" (624 observations), "Web browser software" (430 observations), "Word processing software" (297 observations), and "Email software" (276 observations) are basic digital skills that are used nowadays in most workplaces by the majority of workers (Preeta Goshal FMD Group, 2023 https://www.fdmgroup.com/blog/essential-digital-skills/). Among the top ten most frequent competencies, only "Microsoft Access" (624 observations) and "SAP software" (279 observations) can be considered more specific and less common among occupations.

In Table 2 there are several expertises that are very similar, if not identical, to others present in the same table. This is the case of “Email software” (276 observations), “Microsoft Outlook” (624 observations), and “IBM Notes” (104 observations), which are all email clients and are classified as “Electronic mail software” under the commodity title column, but they differ by being either company-specific or a generic name for an email client. Other examples of extremely similar skills are “Microsoft Word” (783 observations), “Word processing software” (297 observations), “Google Docs” (106 observations), and “Apple iWork Pages” (5 observations), as well as “Web browser software” (430 observations), “Microsoft Internet Explorer” (61 observations), “Internet browser software” (28 observations), and “Mozilla Firefox” (14 observations). The first group is made of software that allow to process and edit texts on computers, while in the second group there are applications for accessing the Internet.

The reason behind the presence of skills so alike can be traced to the data collection process implemented by O*Net occupational analysts. Since O*Net doesn’t elaborate how they’ve come to these peculiar results, an explanation could be that different online sources use different synonyms for the same skill, or in some cases those sources specify that some jobs require knowing how to use a software of a certain company in particular and not just a generic software with the same purpose. For instance, O*Net could have found online job postings that distinctly ask their candidates to know how to use Microsoft Outlook and not IBM Notes or any other email client, or that ask them to know both. In fact, many occupations listed possess two or more similar skills. For example, “Human Resources Specialists” include as software for writing and editing texts digitally both Microsoft Word and Google Docs.

One last thing to remark about Table 2 is the ambiguity of two skills in particular. These skills are “Microsoft Windows” (234 observations) and “Apple MacOS” (57 observations). These are the two most popular operative systems for computers in the world and the great majority of other software listed are designed for both of them. Therefore, it’s not clear at first sight if these competencies refer to knowing how to deal with the architecture of these operating systems or if they simply refer to being able to use a computer.

By looking at the jobs these expertises are associated with on the Technology Skills file, one can see how most of them are not high-tech jobs whose tasks comprehend dealing with operating systems' scripts. To give an idea, jobs that include one of these two skills are, among others, "Advertising and Promotions Managers", "Fitness and Wellness Coordinators", "Talent Directors", and "Registered Nurses".

Since these skills are included also in typically high-tech jobs such as "Network and Computer Systems Administrators and Computer Network Architects", they have to be interpreted both as knowing how to use a personal computer and how to deal with the operating system's architecture, depending on the occupation they are associated with.

## 2.2 Jobs by number of digital skills

The third analysis to be implemented was the classification of jobs by the number of digital skills they're associated with. This third investigation simply consisted of listing all the jobs present in the Technology Skills database by the number of their digital skills, in a descending order.

This table as well is not fully copied here since it's too long. Instead, a smaller table containing only the first 50 occupations by number of skills is here included.

| Job title | Number of digital skills |
|---|---|
| Software Quality Assurance Analysts and Testers | 425 |
| Software Developers | 416 |
| Information Technology Project Managers | 333 |
| Database Architects | 319 |
| Computer Systems Analysts | 310 |
| Computer Programmers | 293 |
| Computer Network Architects | 284 |
| Database Administrators | 282 |
| Network and Computer Systems Administrators | 265 |
| Computer User Support Specialists | 263 |
| Computer Systems Engineers/Architects | 259 |
| Web Developers | 247 |

| | |
|---|---|
| Information Security Analysts | 244 |
| Accountants and Auditors | 238 |
| Web and Digital Interface Designers | 235 |
| Management Analysts | 216 |
| Business Intelligence Analysts | 196 |
| Financial Risk Specialists | 187 |
| Financial and Investment Analysts | 180 |
| Computer and Information Systems Managers | 177 |
| Human Resources Specialists | 173 |
| Data Warehousing Specialists | 157 |
| Hydrologists | 155 |
| Marketing Managers | 149 |
| Market Research Analysts and Marketing Specialists | 148 |
| General and Operations Managers | 146 |
| Geoscientists, Except Hydrologists and Geographers | 142 |
| Computer and Information Research Scientists | 142 |
| Computer Network Support Specialists | 142 |
| Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products | 141 |
| Bioengineers and Biomedical Engineers | 139 |
| Special Effects Artists and Animators | 132 |
| Architectural and Engineering Managers | 131 |
| Geographic Information Systems Technologists and Technicians | 129 |
| Secretaries and Administrative Assistants, Except Legal, Medical, and Executive | 128 |
| Medical and Health Services Managers | 127 |
| Lawyers | 127 |
| Electrical Engineers | 121 |
| Bookkeeping, Accounting, and Auditing Clerks | 120 |
| Training and Development Specialists | 118 |
| Computer Hardware Engineers | 116 |
| Customer Service Representatives | 113 |
| Operations Research Analysts | 112 |
| Medical Records Specialists | 111 |
| Industrial Engineering Technologists and Technicians | 111 |
| Web Administrators | 110 |
| Health Information Technologists and Medical Registrars | 110 |
| Validation Engineers | 109 |
| Transportation, Storage, and Distribution Managers | 108 |
| First-Line Supervisors of Retail Sales Workers | 108 |

*Table 3 Jobs by number of digital skills. Source: personal elaboration*

In total there are 923 different occupations with 32.384 total observations.

At first sight, the results presented in Table 3 don't surprise much. As expected, occupations with the highest number of digital skills are also occupations that are commonly considered high-tech jobs. This is the case of occupations like "Software Quality Assurance Analysts and Testers" (425 skills), "Software Developers" (416 skills), "Information Technology Project Managers" (333 skills), and "Database Architects" (319 skills).

By scrolling down the results listed in Table 3, there can be found some occupations with a relatively high number of technology skills, but that are not generally considered digital jobs, because of the tasks carried out and the educational requirements. Illustrative are the cases of professions like "Accountants and Auditors" (238 skills), "Financial Risk Specialists" (187 skills), "Humar Resources Specialists" (173 skills), as well as "Hydrologists" (155 skills).

By scrolling down even further in the original table, one can notice that there's a similar issue in understanding the results. There are some occupations that show the opposite characteristics to the ones enumerated earlier; they are generally considered as high-tech jobs, but here in the list they happen to be associated with relatively few digital skills. For instance, can be considered as such professions like "Robotics Engineers" (67 skills), "Video Game Designers" (52 skills), "Bioinformatics technicians" (50 skills), and "Blockchain Engineers" (45 skills).

To try to understand the reason behind this seemingly inexplicable characteristic of the database, one more analysis was carried out.
This time the "in demand" column was taken into consideration. According to O*Net database, are considered in demand those software and technology requirements frequently included in the employer job postings for a particular occupation. Therefore, in demand skills can be deemed as more essential than the others to a specific profession.

The first analysis to be conducted regarding in demand skills simply consisted of enumerating in descending order jobs by number of in demand digital skills.
The results are summed up in the following graph, where fifteen jobs with the most in demand digital skills are listed.

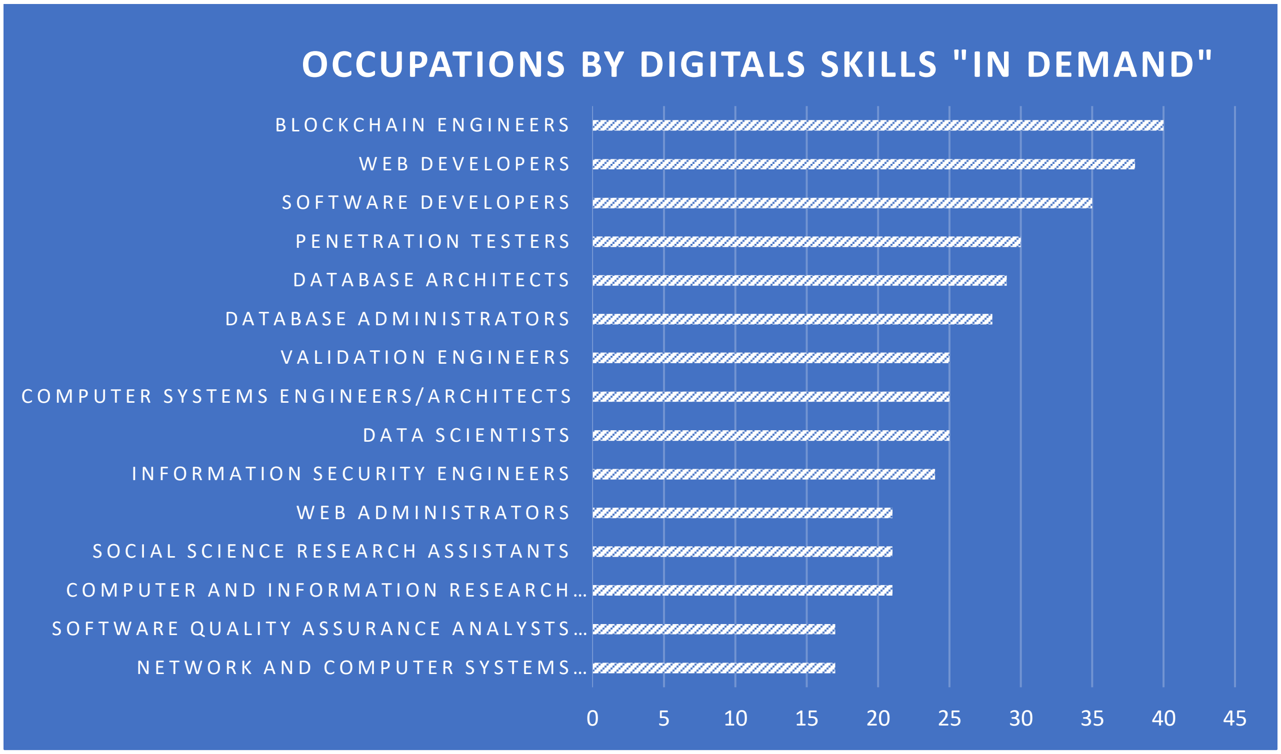


*Figure 2 Jobs by number of in demand digital skills. Source: personal elaboration*

Many of the professions that are present in the figure above are also top jobs by number of digital skills, with no distinction between in demand and not in demand. There are though some exceptions. The most evident one is definitely “Blockchain Engineers” since it’s the occupation with the highest number of in demand technology skills, but in Table 3 it’s associated with only 45 skills. Also “Penetration Testers”, “Information Security Engineers”, and “Validation Engineers” have relatively few digital skills, with respectively 61, 90, and 109 skills each.

To investigate on this characteristic of the database even furhter, a scatter plot that compares each profession's total number of in demand skills with its overall number of digital skills was created. The results of this further analysis is summarized in Figure 3.

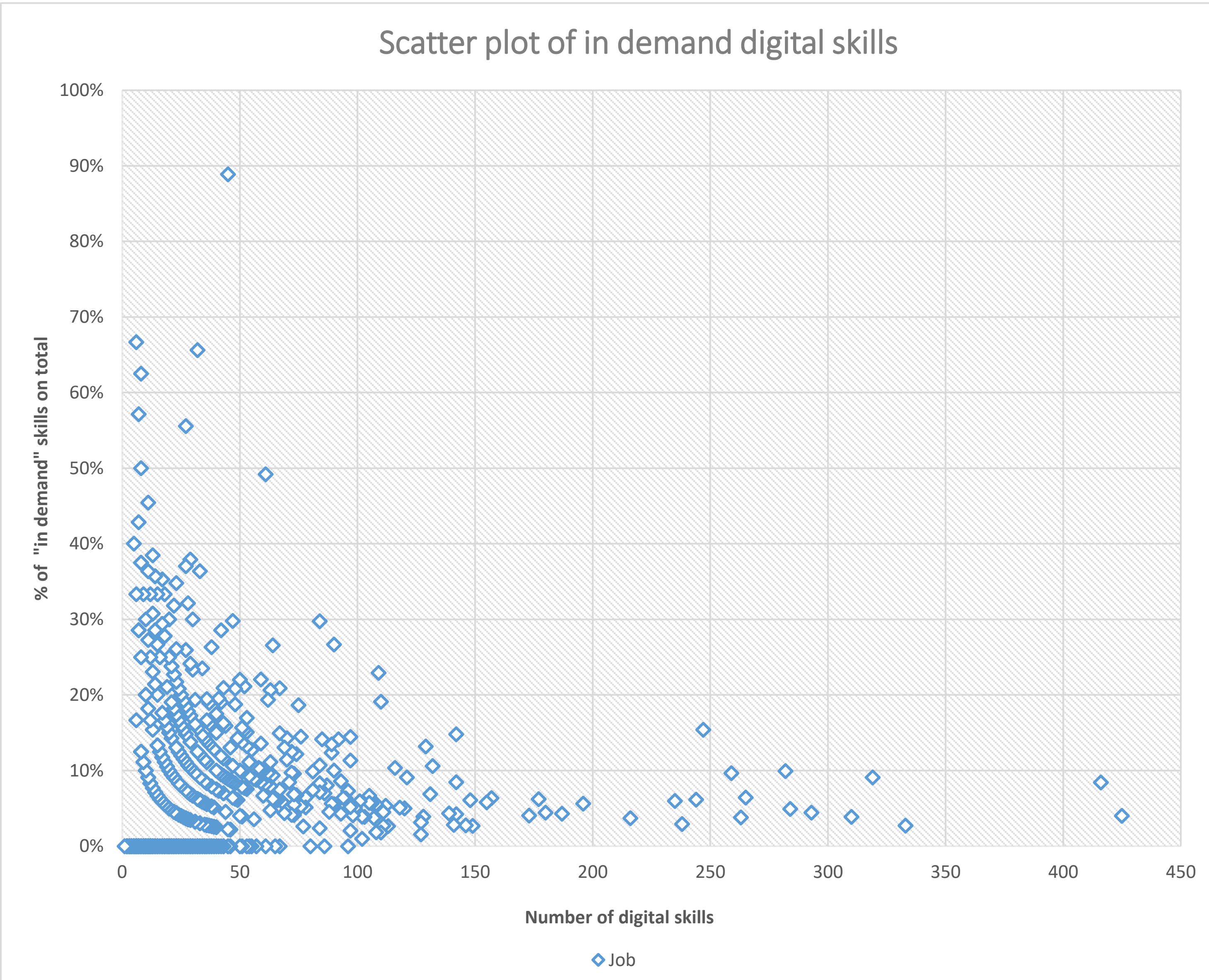


*Figure 3 Scatter plot of in demand digital skills. Source: personal elaboration*

Figure 3 shows that the number of digital skills of a job and the percentage of those same digital skills being in demand are not two directly proportional measures. Instead, they almost seem to be related by an inverse proportion relationship.

There are some professions that have few digital skills in total, but more than 30% of them are often required by employers. There are also some occupations that lie in the bottom-right corner of the graph, meaning that they involve numerous digital skills, but only a small fraction of those skills are considered vital by employers.

The vast majority of occupations though lie in the bottom- left corner, which implies that their total number of skills range from 0 to 100 and up to 30% of them are in demand.

It is also important to highlight how there are several jobs that are positioned on the *x* axis, meaning that none of the skills they're associated with are considered in demand. It's interesting to note that many of these jobs show very few skills in the original dataset, which can reasonably lead to think that they're not typical digital occupations, but rather blue-collar jobs.

This last analysis helps to understand that the Technology Skill database has not to be intended as a list of all digital skills that a person needs to possess in order to be able to perform a certain job, but rather as an enumeration of all digital skills that can be used in a certain profession.

Therefore, the fact that some traditional occupations have relatively many digital skills, while some high-tech jobs have relatively few ones can be explained by the first having many software that have the same functions thus being interchangeable, while the latter use few but very specific software. Moreover, another reason could be traced in the data sources. Online sources could indicate few digital skills for some high-tech jobs simply because these employers give basic skills for granted and therefore list only the expertise they deem essential, while traditional jobs' employers prefer to list more in the details the software that might be use for work probably because they're targeting an audience with a different and not high-tech educational background.

# CHAPTER 3: CLUSTER ANALYSIS

Chapter 3 contains three distinct cluster analyses carried out to assess if jobs that are considered similar can be considered as such also on the basis of the digital skills they involve and, by contrast, if occupations that are normally regarded as not related share in fact many digital skills.
These analyses were realized using different machine learning algorithms. These algorithms are *k*-means, Principal Component Analysis (PCA), and Support Vector Machine. All of them were calculated using RStudio.
Eventually, one last algorithm was added to the thesis. That is a simple predictive algorithm that is based on the *k*-means analyses and that aims to look at the occupation-digital skills relationship from the opposite perspective. This means starting from a list of digital skills to see what cluster that hypothetical job described by those skills would be part of.
Given the importance of the following part of the thesis, it was opted for reporting here as many results as possible. This is true especially for the *k*-means clustering, for which the whole tables for the clusters are copied, with only the tables containing the associated digital skills being partial as they include only the most frequent ones.
For the PCA and for the SVM analysis the outcomes are reported only as graphs.

## 3.1 K-means cluster analysis

The first cluster analysis which was undertaken is the *k*-means analysis. This type of clustering consists of partitioning occupations into groups on the basis of similar digital skills required by those jobs. In order to have more indicative outcomes, only specific skills that are listed under the “Example” column in the Technology Skills database were taken into consideration. Whereas generic digital skills that are categorized according to the UNSPSC and that go under the “Commodity Title” column were not considered, given that they would have led to too broad results which would have been difficult to interpret.

K-means clustering is a method of vector quantization that aims to partition *n* observations into *k* clusters, where each observation belongs to a cluster depending on the distance of it from the cluster's center. The distance of every observation from its cluster's center is less than the distance of it from any other cluster's one.
Since the variables considered for this analysis are categorical, in order to calculate these distances a binary matrix was first constructed with RStudio. This matrix consists of a two ways table with jobs as rows and skills as column; each skill then assumes value 1 when it's associated with that job, while it is 0 when it's not.

The number *n* of observation is given and totals 923, since it is the amount of different jobs listed in the database. On the other hand, the number *k* representing the quantity of clusters is not given, but it must be chosen.

From a rational point of view, the most precise cluster analysis is the one where *k* equals *n*. In this case, every cluster would be made of just one job and therefore the vectorial distance between each clusters' centroid and their only observation would be zero. This analysis would have no meaning as it would just give back the starting data and would not tell which jobs are similar in terms of digital skills.
At the same time, partitioning observations into very few clusters would mean dealing with the opposite issue, as those cluster would be too big and not meaningful at all, since many observations would be grouped together mainly not because they would be similar, but rather because they would be less dissimilar than the elements that would be in the other groups.
Therefore, when picking *k*, it is necessary to balance precision and meaningfulness of clusters by choosing the right number of clusters so that there are not too many nor too few.

To choose *k*, four distinct aspects of the cluster analysis were taken into consideration. These aspects are:

- Sum of all jobs' distances from their clusters' centroids

- Each cluster's total distance between jobs and their center

- Size of each cluster in terms of how many jobs make up the cluster
- Ratio between each cluster's total distance and its size

To reach what can be considered as the right number of clusters, six attempts were made that consisted of computing the elements listed before with different number of clusters. The computations were conducted with the number of clusters going from 5 to 10.

| *k* | Total distance | Clusters' distance | Size | Clusters' distance/size |
|---|---|---|---|---|
| 5 | 23.037,90 | 1464,21 2178,64 1846,06<br>12021,80 5527,19 | 29 31 18<br>739 106 | 50,49 70,28 102;56 16,27 52,14 |
| 6 | 22.582,57 | 1422,14 2178,64 1846,06<br>479,24 5468,92 11187,66 | 28 31 18<br>37 104<br>705 | 50,79 70,28 102,56 12,95<br>52,59 15,87 |
| 7 | 22.158,87 | 1448,41 8707,56 1621,56<br>479,24 4302,21 3753,82<br>1846,05 | 29 361<br>23 37 82<br>373 18 | 49,94 24,12 70,50 12,95<br>52,47 10,06 102,56 |
| 8 | 21.931,57 | 1168,23 2548,30 1409,68<br>6944,00 4202,71 3333,25<br>1846,06 479,24 | 22 50 19<br>359 80<br>338 18<br>37 | 53,10 50,97 74,19 19,34<br>52,53 9,86 102,56 12,95 |
| 9 | 21.754,67 | 360,80 2330,89 1319,11<br>7013,84 4239,63 3046,05<br>1846,05 479,24 1119,05 | 20 45 18<br>353 81<br>330 18<br>37 21 | 18,04 51,80 73,28 19,87<br>52,34 9,23 102,56 12,95<br>53,29 |
| 10 | 21.450,74 | 360,80 2509,59 1409,68<br>6164,05 4030,66 2454,95<br>1596,31 479,24 1248,00<br>1197,44 | 20 49<br>19 367<br>85 287<br>16 37<br>25 18 | 18,04 51,22 74,19 16,80<br>47,42 8,55 99,77 12,95<br>49,92 66,52 |

*Table 4 Summary of cluster analysis' results. Source: personal elaboration*

Table 4 summarizes the results of the calculations aforementioned. Results are listed in order, which means that the first result in each column corresponds to cluster number 1, the second to cluster number 2, the third to cluster number 3, and so on. It can be noticed that some results are the same with different *k* although the position is different. This doesn't change anything, meaning that their elements are still the same.

As expected, the sum of all observations' distances from their clusters' centroids decreases when *k* increases. This generally applies also to clusters' distances and clusters' distances on clusters' sizes as they also tend to decrease on average.

The two most relevant aspects among these are the size and the ratio between a cluster's distance and its size. The size of a cluster is indicative of how RStudio partitions jobs, as it can be seen which groups change the most when *k* increases. On the other hand, clusters' distances on clusters' sizes tells a lot about how homogeneous each cluster is. The lower is the ratio, the more homogeneous is the group.

After these considerations, the chosen number of clusters to calculate for the analysis was 7. This conclusion came up for two main reasons: first, with *k*=7 the huge cluster made of 705 observations that can be seen with *k*=6 is divided into two groups of 361 and 373 occupations each, while distance on size that doesn't change much either with respectively ratios of 24,12 and 10,06 versus 15,85; second, distance on cluster size ratios don't change much with *k*>7.

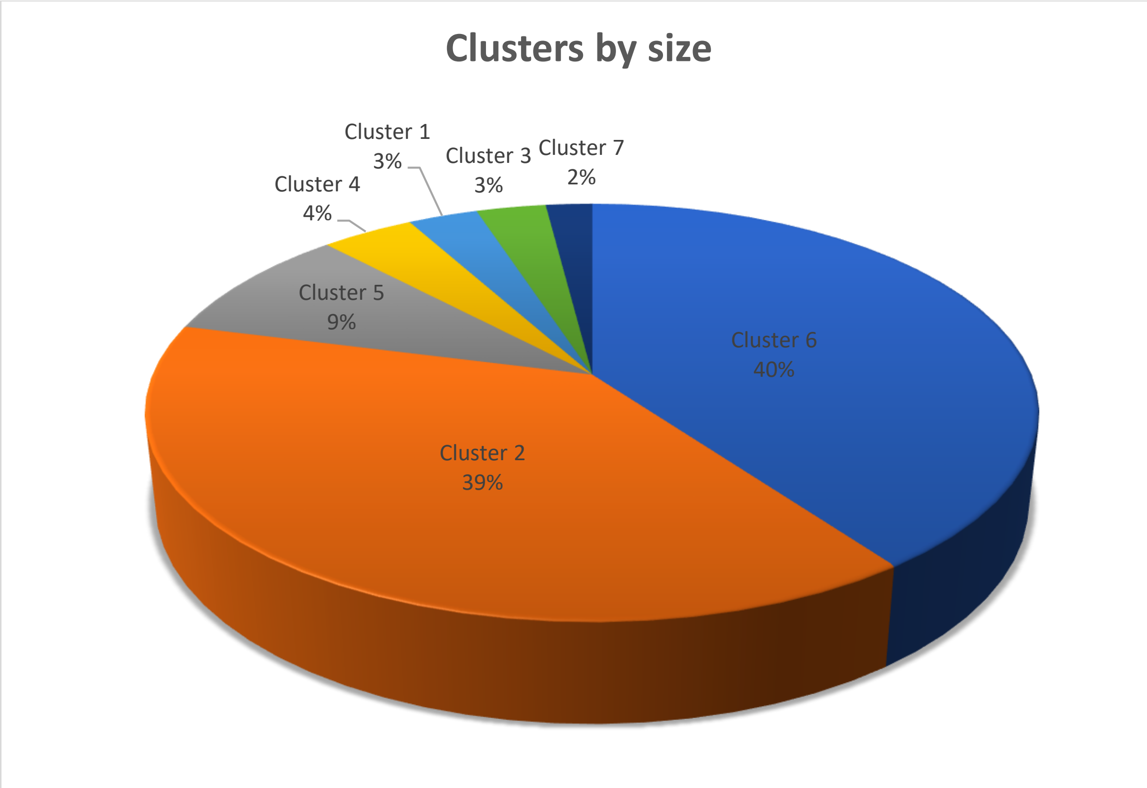


*Figure 4 Graphical representation of clusters sizes. Source: personal elaboration*

### *3.1.1 Cluster 1*

| Occupations |
|---|
| Advertising and Promotions Managers |
| Public Relations Managers |
| Fundraising Managers |
| Training and Development Managers |
| Education Administrators, Postsecondary |
| Meeting, Convention, and Event Planners |
| Training and Development Specialists |
| Search Marketing Strategists |
| Online Merchants |
| Web Administrators |
| Document Management Specialists |
| Librarians and Media Collections Specialists |
| Instructional Coordinators |

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|---|
| Art Directors |
| Fine Artists, Including Painters, Sculptors, and Illustrators |
| Special Effects Artists and Animators |
| Commercial and Industrial Designers |
| Graphic Designers |
| Producers and Directors |
| News Analysts, Reporters, and Journalists |
| Public Relations Specialists |
| Editors |
| Technical Writers |
| Writers and Authors |
| Photographers |
| Film and Video Editors |
| Retail Salespersons |
| Desktop Publishers |
| Proofreaders and Copy Markers |

*Table 5 List of jobs that are part of cluster 1. Source: personal elaboration*

| **Occupations** | **Frequency** |
|---|---|
| Microsoft Word | 29 |
| Microsoft PowerPoint | 28 |
| Microsoft Excel | 28 |
| Adobe Systems Adobe Photoshop | 28 |
| Microsoft Office software | 27 |
| Hypertext markup language HTML | 25 |
| Adobe Systems Adobe InDesign | 24 |
| Microsoft Outlook | 23 |
| Adobe Systems Adobe Dreamweaver | 23 |
| Adobe Systems Adobe Illustrator | 23 |
| Adobe Systems Adobe Acrobat | 23 |
| Microsoft Access | 21 |
| Adobe Systems Adobe Creative Cloud software | 21 |
| Web browser software | 20 |
| Microsoft Project | 20 |
| Adobe Systems Adobe After Effects | 20 |
| Apple Final Cut Pro | 19 |
| JavaScript | 18 |
| Facebook | 18 |
| YouTube | 17 |
| Microsoft Publisher | 17 |
| Drupal | 17 |

| | |
|---|---|
| FileMaker Pro | 15 |
| Microsoft Visio | 15 |
| Microsoft SharePoint | 15 |
| WordPress | 14 |
| Extensible markup language XML | 14 |
| Cascading style sheets CSS | 14 |
| Adobe Systems Adobe Fireworks | 14 |
| PHP | 12 |
| QuarkXPress | 12 |
| Social media sites | 12 |
| Microsoft Dynamics | 12 |
| Google Drive | 12 |
| LinkedIn | 12 |
| Google Ads | 11 |
| Google Analytics | 11 |
| Adobe Systems Adobe ActionScript | 11 |
| Twitter | 10 |
| SmugMug Flickr | 10 |
| Google Docs | 10 |

*Table 6 Most frequent skills associated with jobs of cluster 1 Source: personal elaboration*

Cluster 1 contains 29 occupations, with a total Euclidean distance of 1.448,41. The distance mean is 49,94, meaning that on average a job that is part of this cluster has a vectorial distance of 49,94 from its cluster's center.
Associated with this cluster there are 864 different specific digital skills that represent roughly 10% of total digital skills.
There are in total 2.066 observations of these skills. This entails that each profession on average requires approximately 71 skills.

Most of the jobs that are in the list can be considered creative jobs. Some of them though are not typically creative occupations. This is the case among others of jobs like "Fundraising Managers", "Training and Development Managers", and "Education Administrators, Postsecondary". This can mean that this small group of professions that seems unrelated to the remaining jobs that make up the cluster must share many skills requirements with creative jobs.

Another explanation to having both related and unrelated jobs in the same cluster could be that RStudio, when partitioning jobs into clusters, couldn't find for these occupations any much related group of jobs to put them together and thus opted for grouping them all with the least diverse cluster of professions. However, this cannot be the case for this explanation as cluster 1 has an average distance of 49,94, which although relatively high is not the highest.

The skills that are associated with the jobs that are part of cluster 1 seem to follow the pattern. By looking at the list of the most frequent skills, one can see how, besides the ones that are part of the Microsoft Office suite, many of them are used for creating and editing media content.

### *3.1.2 Cluster 2*

| Occupations |
|---|
| Chief Executives |
| Chief Sustainability Officers |
| Legislators |
| Facilities Managers |
| Security Managers |
| Treasurers and Controllers |
| Investment Fund Managers |
| Industrial Production Managers |
| Quality Control Systems Managers |
| Biofuels Production Managers |
| Hydroelectric Production Managers |
| Purchasing Managers |
| Transportation, Storage, and Distribution Managers |
| Supply Chain Managers |
| Compensation and Benefits Managers |
| Human Resources Managers |
| Farmers, Ranchers, and Other Agricultural Managers |
| Construction Managers |
| Education and Childcare Administrators, Preschool and Daycare |
| Education Administrators, Kindergarten through Secondary |
| Food Service Managers |
| Lodging Managers |

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| Natural Sciences Managers |
| Clinical Research Coordinators |
| Water Resource Specialists |
| Property, Real Estate, and Community Association Managers |
| Social and Community Service Managers |
| Emergency Management Directors |
| Funeral Home Managers |
| Fitness and Wellness Coordinators |
| Regulatory Affairs Managers |
| Compliance Managers |
| Loss Prevention Managers |
| Wind Energy Operations Managers |
| Wind Energy Development Managers |
| Brownfield Redevelopment Specialists and Site Managers |
| Agents and Business Managers of Artists, Performers, and Athletes |
| Buyers and Purchasing Agents, Farm Products |
| Wholesale and Retail Buyers, Except Farm Products |
| Purchasing Agents, Except Wholesale, Retail, and Farm Products |
| Claims Adjusters, Examiners, and Investigators |
| Insurance Appraisers, Auto Damage |
| Compliance Officers |
| Environmental Compliance Inspectors |
| Equal Opportunity Representatives and Officers |
| Government Property Inspectors and Investigators |
| Coroners |
| Regulatory Affairs Specialists |
| Customs Brokers |
| Cost Estimators |
| Farm Labor Contractors |
| Labor Relations Specialists |
| Logisticians |
| Logistics Analysts |
| Fundraisers |
| Compensation, Benefits, and Job Analysis Specialists |
| Business Continuity Planners |
| Sustainability Specialists |
| Security Management Specialists |
| Appraisers of Personal and Business Property |
| Appraisers and Assessors of Real Estate |
| Budget Analysts |
| Credit Analysts |
| Personal Financial Advisors |
| Insurance Underwriters |

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|---|
| Financial Examiners |
| Credit Counselors |
| Loan Officers |
| Tax Examiners and Collectors, and Revenue Agents |
| Fraud Examiners, Investigators and Analysts |
| Architects, Except Landscape and Naval |
| Landscape Architects |
| Cartographers and Photogrammetrists |
| Geodetic Surveyors |
| Agricultural Engineers |
| Transportation Engineers |
| Water/Wastewater Engineers |
| Fire-Prevention and Protection Engineers |
| Marine Engineers and Naval Architects |
| Fuel Cell Engineers |
| Mining and Geological Engineers, Including Mining Safety Engineers |
| Energy Engineers, Except Wind and Solar |
| Architectural and Civil Drafters |
| Mechanical Drafters |
| Civil Engineering Technologists and Technicians |
| Non-Destructive Testing Specialists |
| Photonics Technicians |
| Surveying and Mapping Technicians |
| Animal Scientists |
| Food Scientists and Technologists |
| Soil and Plant Scientists |
| Microbiologists |
| Zoologists and Wildlife Biologists |
| Molecular and Cellular Biologists |
| Conservation Scientists |
| Park Naturalists |
| Foresters |
| Epidemiologists |
| Environmental Scientists and Specialists, Including Health |
| Environmental Restoration Planners |
| Geoscientists, Except Hydrologists and Geographers |
| Hydrologists |
| Industrial-Organizational Psychologists |
| Clinical and Counseling Psychologists |
| School Psychologists |
| Sociologists |
| Urban and Regional Planners |
| Anthropologists and Archeologists |

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| Geographers |
| Historians |
| Political Scientists |
| Transportation Planners |
| Agricultural Technicians |
| Precision Agriculture Technicians |
| Food Science Technicians |
| Biological Technicians |
| Chemical Technicians |
| Environmental Science and Protection Technicians, Including Health |
| Geological Technicians, Except Hydrologic Technicians |
| Hydrologic Technicians |
| Nuclear Technicians |
| Nuclear Monitoring Technicians |
| Forest and Conservation Technicians |
| Forensic Science Technicians |
| Occupational Health and Safety Specialists |
| Occupational Health and Safety Technicians |
| Substance Abuse and Behavioral Disorder Counselors |
| Educational, Guidance, and Career Counselors and Advisors |
| Marriage and Family Therapists |
| Mental Health Counselors |
| Rehabilitation Counselors |
| Child, Family, and School Social Workers |
| Healthcare Social Workers |
| Mental Health and Substance Abuse Social Workers |
| Health Education Specialists |
| Probation Officers and Correctional Treatment Specialists |
| Social and Human Service Assistants |
| Community Health Workers |
| Clergy |
| Directors, Religious Activities and Education |
| Lawyers |
| Judicial Law Clerks |
| Administrative Law Judges, Adjudicators, and Hearing Officers |
| Arbitrators, Mediators, and Conciliators |
| Judges, Magistrate Judges, and Magistrates |
| Paralegals and Legal Assistants |
| Title Examiners, Abstractors, and Searchers |
| Elementary School Teachers, Except Special Education |
| Middle School Teachers, Except Special and Career/Technical Education |
| Special Education Teachers, Preschool |
| Special Education Teachers, Kindergarten |

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|---|
| Special Education Teachers, Elementary School |
| Special Education Teachers, Secondary School |
| Adapted Physical Education Specialists |
| Adult Basic Education, Adult Secondary Education, and English as a Second Language Instructors |
| Self-Enrichment Teachers |
| Archivists |
| Curators |
| Museum Technicians and Conservators |
| Library Technicians |
| Farm and Home Management Educators |
| Teaching Assistants, Preschool, Elementary, Middle, and Secondary School, Except Special Education |
| Teaching Assistants, Special Education |
| Fashion Designers |
| Floral Designers |
| Interior Designers |
| Merchandise Displayers and Window Trimmers |
| Actors |
| Media Programming Directors |
| Talent Directors |
| Coaches and Scouts |
| Umpires, Referees, and Other Sports Officials |
| Choreographers |
| Broadcast Announcers and Radio Disc Jockeys |
| Interpreters and Translators |
| Audio and Video Technicians |
| Broadcast Technicians |
| Sound Engineering Technicians |
| Lighting Technicians |
| Dietitians and Nutritionists |
| Pharmacists |
| Anesthesiologist Assistants |
| Low Vision Therapists, Orientation and Mobility Specialists, and Vision Rehabilitation Therapists |
| Recreational Therapists |
| Exercise Physiologists |
| Art Therapists |
| Veterinarians |
| Registered Nurses |
| Acute Care Nurses |
| Clinical Nurse Specialists |
| Nurse Practitioners |
| Anesthesiologists |
| Preventive Medicine Physicians |
| Medical and Clinical Laboratory Technologists |

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|---|
| Cytogenetic Technologists |
| Medical and Clinical Laboratory Technicians |
| Dietetic Technicians |
| Veterinary Technologists and Technicians |
| Ophthalmic Medical Technicians |
| Licensed Practical and Licensed Vocational Nurses |
| Medical Records Specialists |
| Orthotists and Prosthetists |
| Neurodiagnostic Technologists |
| Ophthalmic Medical Technologists |
| Patient Representatives |
| Health Information Technologists and Medical Registrars |
| Athletic Trainers |
| Genetic Counselors |
| Home Health Aides |
| Occupational Therapy Assistants |
| Occupational Therapy Aides |
| Physical Therapist Assistants |
| Medical Assistants |
| Medical Equipment Preparers |
| Medical Transcriptionists |
| Pharmacy Aides |
| Veterinary Assistants and Laboratory Animal Caretakers |
| First-Line Supervisors of Correctional Officers |
| First-Line Supervisors of Police and Detectives |
| First-Line Supervisors of Firefighting and Prevention Workers |
| First-Line Supervisors of Security Workers |
| Firefighters |
| Fire Inspectors and Investigators |
| Forest Fire Inspectors and Prevention Specialists |
| Bailiffs |
| Correctional Officers and Jailers |
| Detectives and Criminal Investigators |
| Police Identification and Records Officers |
| Fish and Game Wardens |
| Parking Enforcement Workers |
| Police and Sheriff's Patrol Officers |
| Transit and Railroad Police |
| Animal Control Workers |
| Private Detectives and Investigators |
| Retail Loss Prevention Specialists |
| First-Line Supervisors of Food Preparation and Serving Workers |
| First-Line Supervisors of Housekeeping and Janitorial Workers |

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|---|
| First-Line Supervisors of Gambling Services Workers |
| Animal Trainers |
| Animal Caretakers |
| Motion Picture Projectionists |
| Concierges |
| Tour Guides and Escorts |
| Travel Guides |
| Exercise Trainers and Group Fitness Instructors |
| Recreation Workers |
| Residential Advisors |
| First-Line Supervisors of Non-Retail Sales Workers |
| Counter and Rental Clerks |
| Parts Salespersons |
| Advertising Sales Agents |
| Insurance Sales Agents |
| Travel Agents |
| Sales Representatives of Services, Except Advertising, Insurance, Financial Services, and Travel |
| Solar Sales Representatives and Assessors |
| Demonstrators and Product Promoters |
| Real Estate Brokers |
| Real Estate Sales Agents |
| Switchboard Operators, Including Answering Service |
| Telephone Operators |
| Bill and Account Collectors |
| Billing and Posting Clerks |
| Payroll and Timekeeping Clerks |
| Procurement Clerks |
| Tellers |
| Brokerage Clerks |
| Correspondence Clerks |
| Court, Municipal, and License Clerks |
| Credit Authorizers, Checkers, and Clerks |
| Eligibility Interviewers, Government Programs |
| File Clerks |
| Interviewers, Except Eligibility and Loan |
| Library Assistants, Clerical |
| Loan Interviewers and Clerks |
| New Accounts Clerks |
| Order Clerks |
| Human Resources Assistants, Except Payroll and Timekeeping |
| Receptionists and Information Clerks |
| Reservation and Transportation Ticket Agents and Travel Clerks |
| Cargo and Freight Agents |

| |
|---|
| Freight Forwarders |
| Public Safety Telecommunicators |
| Dispatchers, Except Police, Fire, and Ambulance |
| Meter Readers, Utilities |
| Production, Planning, and Expediting Clerks |
| Shipping, Receiving, and Inventory Clerks |
| Weighers, Measurers, Checkers, and Samplers, Recordkeeping |
| Legal Secretaries and Administrative Assistants |
| Medical Secretaries and Administrative Assistants |
| Data Entry Keyers |
| Word Processors and Typists |
| Insurance Claims and Policy Processing Clerks |
| Mail Clerks and Mail Machine Operators, Except Postal Service |
| Office Machine Operators, Except Computer |
| First-Line Supervisors of Farming, Fishing, and Forestry Workers |
| Agricultural Inspectors |
| Animal Breeders |
| Graders and Sorters, Agricultural Products |
| Forest and Conservation Workers |
| Log Graders and Scalers |
| First-Line Supervisors of Construction Trades and Extraction Workers |
| Solar Energy Installation Managers |
| Electricians |
| Solar Thermal Installers and Technicians |
| Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters |
| Helpers--Carpenters |
| Construction and Building Inspectors |
| Hazardous Materials Removal Workers |
| Highway Maintenance Workers |
| Weatherization Installers and Technicians |
| Excavating and Loading Machine and Dragline Operators, Surface Mining |
| Roustabouts, Oil and Gas |
| First-Line Supervisors of Mechanics, Installers, and Repairers |
| Computer, Automated Teller, and Office Machine Repairers |
| Avionics Technicians |
| Electric Motor, Power Tool, and Related Repairers |
| Security and Fire Alarm Systems Installers |
| Aircraft Mechanics and Service Technicians |
| Control and Valve Installers and Repairers, Except Mechanical Door |
| Heating, Air Conditioning, and Refrigeration Mechanics and Installers |
| Industrial Machinery Mechanics |
| Maintenance Workers, Machinery |
| Medical Equipment Repairers |

| |
|---|
| Maintenance and Repair Workers, General |
| Wind Turbine Service Technicians |
| Helpers--Installation, Maintenance, and Repair Workers |
| First-Line Supervisors of Production and Operating Workers |
| Team Assemblers |
| Machinists |
| Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic |
| Tool and Die Makers |
| Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders |
| Prepress Technicians and Workers |
| Printing Press Operators |
| Woodworking Machine Setters, Operators, and Tenders, Except Sawing |
| Power Distributors and Dispatchers |
| Power Plant Operators |
| Stationary Engineers and Boiler Operators |
| Water and Wastewater Treatment Plant and System Operators |
| Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders |
| Mixing and Blending Machine Setters, Operators, and Tenders |
| Inspectors, Testers, Sorters, Samplers, and Weighers |
| Dental Laboratory Technicians |
| Packaging and Filling Machine Operators and Tenders |
| Photographic Process Workers and Processing Machine Operators |
| Computer Numerically Controlled Tool Operators |
| Computer Numerically Controlled Tool Programmers |
| Tire Builders |
| Helpers--Production Workers |
| First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand |
| Recycling Coordinators |
| First-Line Supervisors of Material-Moving Machine and Vehicle Operators |
| First-Line Supervisors of Passenger Attendants |
| Air Traffic Controllers |
| Airfield Operations Specialists |
| Sailors and Marine Oilers |
| Ship Engineers |
| Traffic Technicians |
| Aviation Inspectors |
| Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation |
| Stockers and Order Fillers |

*Table 7 List of jobs that are part of cluster 2. Source: personal elaboration*

| Skills | Frequency |
|---|---|
| Microsoft Excel | 361 |
| Microsoft Word | 360 |
| Microsoft Office software | 356 |
| Microsoft PowerPoint | 351 |
| Microsoft Outlook | 335 |
| Microsoft Access | 227 |
| Web browser software | 224 |
| Word processing software | 200 |
| SAP software | 147 |
| Email software | 142 |
| Microsoft Windows | 101 |
| Database software | 99 |
| Microsoft Project | 94 |
| Adobe Systems Adobe Acrobat | 87 |
| Spreadsheet software | 86 |
| Microsoft SharePoint | 78 |
| Autodesk AutoCAD | 77 |
| Adobe Systems Adobe Photoshop | 59 |
| Structured query language SQL | 56 |
| Microsoft Visio | 51 |
| Microsoft Dynamics | 50 |
| Facebook | 46 |
| Enterprise resource planning ERP software | 42 |
| Corel WordPerfect Office Suite | 42 |
| Intuit QuickBooks | 41 |
| Scheduling software | 40 |
| ESRI ArcGIS software | 39 |
| Microsoft Internet Explorer | 37 |
| Microsoft Publisher | 37 |
| FileMaker Pro | 36 |
| Adobe Systems Adobe InDesign | 36 |
| Adobe Systems Adobe Illustrator | 35 |
| IBM Notes | 34 |
| Geographic information system GIS software | 34 |
| Graphics software | 34 |
| Operating system software | 33 |
| Geographic information system GIS systems | 31 |
| Oracle PeopleSoft | 30 |
| SAS | 29 |
| Oracle JD Edwards EnterpriseOne | 29 |
| ESRI ArcView | 27 |
| Oracle Database | 26 |
| Linux | 25 |

| | |
|---|---|
| MEDITECH software | 25 |
| Healthcare common procedure coding system HCPCS | 25 |
| Google Docs | 24 |
| Supervisory control and data acquisition SCADA software | 23 |
| Salesforce software | 23 |
| Computer aided design CAD software | 23 |
| Microsoft Active Server Pages ASP | 22 |
| Medical procedure coding software | 22 |
| Customer relationship management CRM software | 21 |
| Zoom | 20 |
| Microsoft SQL Server | 20 |
| Medical condition coding software | 20 |
| IBM SPSS Statistics | 20 |
| Bentley MicroStation | 20 |
| Statistical software | 19 |
| Python | 19 |

*Table 8 Most frequent skills associated with jobs of cluster 2. Source: personal elaboration*

Cluster number 2 is the second largest cluster by size, containing 361 jobs. Total distance between each point representing a job and the cluster center is 8.707,56. Hence, the average distance is 24,12.
In this cluster there are 4.250 different skills that are related to at least one occupation of the cluster. This means that almost half of all technology skills can be found in this group of jobs. The number of total observations of these competencies equals 11.294. Therefore, each profession of the cluster is associated on average with about 31 digital skills.

When looking at the jobs that compose cluster 2, the most prominent thing is that there is not a single pattern that can be traced. In fact, there are list includes extremely different professions in terms of tasks carried out, educational background, and industry. For instance, in this cluster there are put together jobs like “Epidemiologists”, “Firefighters”, “Historians”, as well as “Real Estate Brokers”. Although, there can be noticed some patterns that concern just a few of the occupations of the cluster. This is the case of some healthcare occupations like “Registered Nurse”, “Preventive Medicine Physician”, and “Neurodiagnostic Technologists”. Other examples among others of similar professions that could hypothetically form some subgroups of the cluster are: “Correctional Officers and Jailers”, “Detectives and Criminal Investigators”, and “Police Identification and Records Officers” as they’re all law enforcement occupations; “Procurement Clerks”, “Brokerage Clerks”, and “File Clerks”, since they’re all clerical jobs.

The fact that a single pattern cannot be traced is reflected also into the list of skills that are associated with the jobs. This can be seen in the total number of different skills, which is the highest among all cluster, meaning that there’s high diversity in the type of software used.

### *3.1.3 Cluster 3*

| Occupations |
|---|
| General and Operations Managers |
| Marketing Managers |
| Sales Managers |
| Administrative Services Managers |
| Financial Managers |
| Entertainment and Recreation Managers, Except Gambling |
| Medical and Health Services Managers |
| Human Resources Specialists |
| Project Management Specialists |
| Market Research Analysts and Marketing Specialists |
| Accountants and Auditors |
| Financial and Investment Analysts |
| Financial Risk Specialists |
| Operations Research Analysts |
| First-Line Supervisors of Retail Sales Workers |
| Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products |
| Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products |
| First-Line Supervisors of Office and Administrative Support Workers |
| Bookkeeping, Accounting, and Auditing Clerks |
| Customer Service Representatives |
| Executive Secretaries and Executive Administrative Assistants |
| Secretaries and Administrative Assistants, Except Legal, Medical, and Executive |
| Office Clerks, General |

*Table 9 List of jobs that are part of cluster 3. Source: personal elaboration*

| Digital skills | Frequency |
|---|---|
| Microsoft Word | 23 |
| Microsoft PowerPoint | 23 |
| Microsoft Office software | 23 |
| IBM Notes | 23 |
| Microsoft SharePoint | 23 |
| Microsoft Dynamics | 23 |
| Microsoft Excel | 23 |
| Microsoft Access | 23 |
| SAP software | 22 |
| Microsoft Outlook | 22 |
| Oracle PeopleSoft | 22 |
| Microsoft Project | 22 |
| FileMaker Pro | 21 |
| Google Docs | 21 |
| Oracle Hyperion | 20 |
| LexisNexis | 20 |
| Salesforce software | 19 |
| Microsoft Visio | 19 |
| IBM SPSS Statistics | 19 |
| Intuit QuickBooks | 19 |
| IBM Cognos Impromptu | 19 |
| Adobe Systems Adobe Acrobat | 19 |
| SAS | 18 |
| NetSuite ERP | 18 |
| Google Drive | 18 |
| SAP Business Objects | 17 |
| Sage 50 Accounting | 17 |
| Qlik Tech QlikView | 17 |
| Oracle JD Edwards EnterpriseOne | 17 |
| Oracle E-Business Suite Financials | 17 |
| Oracle Database | 17 |
| Microsoft Publisher | 17 |
| Microsoft Exchange | 17 |
| Database software | 17 |
| Yardi software | 16 |
| SAP Crystal Reports | 16 |
| Human resource management software HRMS | 16 |
| Microsoft Dynamics GP | 16 |
| Oracle Business Intelligence Enterprise Edition | 16 |
| Oracle PeopleSoft Financials | 16 |
| LinkedIn | 16 |
| Blackbaud The Raiser's Edge | 16 |
| Delphi Technology | 16 |

| | |
|---|---|
| Teradata Database | 15 |
| Tableau | 15 |
| Social media sites | 15 |
| Oracle Primavera Enterprise Project Portfolio Management | 15 |
| MicroStrategy | 15 |
| Microsoft Windows | 15 |
| Oracle Fusion Applications | 15 |

*Table 10 Most frequent skills associated with jobs of cluster 3. Source: personal elaboration*

In total there are 23 professions included in cluster number 3. The sum of all jobs' vectorial distances from the centroid is 1.621,56, with an average distance of 70,50.
The number of digital skills that are related to these occupations is 943 and there are 2.759 observations of these skills. Therefore, each job is associated on average with almost 120 digital skills.

The professions here listed appear to be highly related to each other, as they all related to the administration of different parts of one or more business operations of a commercial enterprise.
The digital skills associated with the jobs of this cluster are consistent with the recognized pattern. In fact, most of them are commonly used for managing businesses or business units.

### *3.1.4 Cluster 4*

| Occupations |
|---|
| Business Teachers, Postsecondary |
| Computer Science Teachers, Postsecondary |
| Mathematical Science Teachers, Postsecondary |
| Architecture Teachers, Postsecondary |
| Engineering Teachers, Postsecondary |
| Agricultural Sciences Teachers, Postsecondary |
| Biological Science Teachers, Postsecondary |
| Forestry and Conservation Science Teachers, Postsecondary |
| Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary |
| Chemistry Teachers, Postsecondary |
| Environmental Science Teachers, Postsecondary |

| |
|---|
| Physics Teachers, Postsecondary |
| Anthropology and Archeology Teachers, Postsecondary |
| Area, Ethnic, and Cultural Studies Teachers, Postsecondary |
| Economics Teachers, Postsecondary |
| Geography Teachers, Postsecondary |
| Political Science Teachers, Postsecondary |
| Psychology Teachers, Postsecondary |
| Sociology Teachers, Postsecondary |
| Health Specialties Teachers, Postsecondary |
| Nursing Instructors and Teachers, Postsecondary |
| Education Teachers, Postsecondary |
| Library Science Teachers, Postsecondary |
| Criminal Justice and Law Enforcement Teachers, Postsecondary |
| Law Teachers, Postsecondary |
| Social Work Teachers, Postsecondary |
| Art, Drama, and Music Teachers, Postsecondary |
| Communications Teachers, Postsecondary |
| English Language and Literature Teachers, Postsecondary |
| Foreign Language and Literature Teachers, Postsecondary |
| History Teachers, Postsecondary |
| Philosophy and Religion Teachers, Postsecondary |
| Family and Consumer Sciences Teachers, Postsecondary |
| Recreation and Fitness Studies Teachers, Postsecondary |
| Career/Technical Education Teachers, Postsecondary |
| Career/Technical Education Teachers, Secondary School |
| Teaching Assistants, Postsecondary |

*Table 11 List of jobs that are part of cluster 4. Source: personal elaboration*

| Digital skills | Frequency |
|---|---|
| Microsoft PowerPoint | 37 |
| Learning management system LMS | 37 |
| Web browser software | 37 |
| Blackboard Learn | 37 |
| Microsoft Office software | 37 |
| Calendar and scheduling software | 37 |
| Microsoft Word | 37 |
| Collaborative editing software | 37 |
| iParadigms Turnitin | 37 |
| Course management system software | 37 |
| Microsoft Excel | 37 |
| Desire2Learn LMS software | 37 |

| | |
|---|---|
| Microsoft Outlook | 37 |
| DOC Cop | 37 |
| Email software | 37 |
| Sakai CLE | 37 |
| Image scanning software | 36 |
| Google Docs | 36 |
| Moodle | 16 |
| Blackboard software | 16 |
| Word processing software | 14 |
| SAS | 9 |
| Adobe Systems Adobe Photoshop | 9 |
| The MathWorks MATLAB | 8 |
| IBM SPSS Statistics | 8 |
| Adobe Systems Adobe Acrobat | 7 |
| Microsoft Access | 7 |
| Geographic information system GIS software | 6 |
| Adobe Systems Adobe Illustrator | 6 |
| ESRI ArcGIS software | 5 |
| JavaScript | 5 |
| R | 5 |
| Adobe Systems Adobe Creative Suite | 5 |
| C++ | 4 |
| Edmodo | 4 |
| Autodesk AutoCAD | 4 |

*Table 12 Most frequent skills associated with jobs of cluster 4. Source: personal elaboration*

Cluster 4 contains 37 professions. The total Euclidean distance is 479,24, while the mean of the distances is 12,95, which makes cluster number 4 the class of jobs with the second lowest average distance.

There are 355 skills that are related to cluster 4's occupations and there are in total 1.192 observation. Thus, each occupation requires on average around 32 digital skills.

Cluster 4 is extremely easy to classify on the basis of the professions it contains since all of them are education and training occupations.

This can be noticed as well in the related skills, as many of them are e-learning software like "Learning Management Software LMS", "Blackboard Learn", and " Desire2Learn LMS Software". Many other software of that list are related to teaching, as for instance "Microsoft

PowerPoint" which is commonly used by teacher and professors to project slides useful for the lesson, or "Google Docs" and "Moodle" that are used for uploading class related material.

### *3.1.5 Cluster 5*

| Occupations |
| --- |
| Architectural and Engineering Managers |
| Biofuels/Biodiesel Technology and Product Development Managers |
| Logistics Engineers |
| Financial Quantitative Analysts |
| Health Informatics Specialists |
| Computer and Information Research Scientists |
| Computer Network Support Specialists |
| Telecommunications Engineering Specialists |
| Video Game Designers |
| Geographic Information Systems Technologists and Technicians |
| Penetration Testers |
| Information Security Engineers |
| Digital Forensics Analysts |
| Blockchain Engineers |
| Actuaries |
| Mathematicians |
| Statisticians |
| Biostatisticians |
| Data Scientists |
| Clinical Data Managers |
| Bioinformatics Technicians |
| Aerospace Engineers |
| Bioengineers and Biomedical Engineers |
| Chemical Engineers |
| Civil Engineers |
| Computer Hardware Engineers |
| Electrical Engineers |
| Electronics Engineers, Except Computer |
| Radio Frequency Identification Device Specialists |
| Environmental Engineers |
| Health and Safety Engineers, Except Mining Safety Engineers and Inspectors |
| Industrial Engineers |
| Human Factors Engineers and Ergonomists |

| |
|---|
| Validation Engineers |
| Manufacturing Engineers |
| Materials Engineers |
| Mechanical Engineers |
| Automotive Engineers |
| Nuclear Engineers |
| Petroleum Engineers |
| Mechatronics Engineers |
| Microsystems Engineers |
| Photonics Engineers |
| Robotics Engineers |
| Nanosystems Engineers |
| Wind Energy Engineers |
| Solar Energy Systems Engineers |
| Electrical and Electronics Drafters |
| Aerospace Engineering and Operations Technologists and Technicians |
| Electrical and Electronic Engineering Technologists and Technicians |
| Electro-Mechanical and Mechatronics Technologists and Technicians |
| Robotics Technicians |
| Environmental Engineering Technologists and Technicians |
| Industrial Engineering Technologists and Technicians |
| Mechanical Engineering Technologists and Technicians |
| Biochemists and Biophysicists |
| Bioinformatics Scientists |
| Geneticists |
| Biologists |
| Range Managers |
| Medical Scientists, Except Epidemiologists |
| Astronomers |
| Physicists |
| Atmospheric and Space Scientists |
| Chemists |
| Climate Change Policy Analysts |
| Industrial Ecologists |
| Remote Sensing Scientists and Technologists |
| Economists |
| Environmental Economists |
| Survey Researchers |
| Social Science Research Assistants |
| Quality Control Analysts |
| Remote Sensing Technicians |
| Career/Technical Education Teachers, Middle School |
| Set and Exhibit Designers |

| |
|---|
| Media Technical Directors/Managers |
| Intelligence Analysts |
| Securities, Commodities, and Financial Services Sales Agents |
| Sales Engineers |
| Statistical Assistants |
| Energy Auditors |

*Table 13 List of jobs that are part of cluster 5. Source: personal elaboration*

| **Digital skills** | **Frequency** |
|---|---|
| Microsoft Office software | 81 |
| Microsoft Excel | 81 |
| Microsoft PowerPoint | 80 |
| Python | 73 |
| Microsoft Word | 71 |
| C++ | 70 |
| The MathWorks MATLAB | 61 |
| Microsoft Access | 60 |
| Linux | 60 |
| Structured query language SQL | 55 |
| Oracle Java | 55 |
| UNIX | 52 |
| Microsoft Visio | 44 |
| Microsoft Outlook | 44 |
| Microsoft Visual Basic | 43 |
| Microsoft Project | 42 |
| SAP software | 41 |
| Perl | 41 |
| Autodesk AutoCAD | 41 |
| SAS | 40 |
| R | 40 |
| C | 38 |
| Web browser software | 37 |
| National Instruments LabVIEW | 37 |
| Microsoft SQL Server | 37 |
| JavaScript | 34 |
| C# | 32 |
| Extensible markup language XML | 31 |
| Dassault Systemes SolidWorks | 31 |
| Word processing software | 30 |
| Microsoft Windows | 28 |
| Minitab | 26 |
| Dassault Systemes CATIA | 26 |

| | |
|---|---|
| Microsoft Visual Studio | 25 |
| IBM SPSS Statistics | 25 |
| ESRI ArcGIS software | 24 |
| Shell script | 22 |
| Oracle Database | 22 |
| Microsoft SharePoint | 22 |
| Git | 22 |
| Formula translation/translator FORTRAN | 22 |
| Computer aided design CAD software | 22 |
| PTC Creo Parametric | 21 |
| Tableau | 19 |
| Wolfram Research Mathematica | 19 |
| Microsoft Azure software | 18 |
| Atlassian JIRA | 18 |
| Adobe Systems Adobe Photoshop | 18 |
| Supervisory control and data acquisition SCADA software | 17 |
| Statistical software | 17 |
| Software development tools | 17 |
| Mathsoft Mathcad | 17 |
| IBM Notes | 17 |
| Bentley MicroStation | 17 |
| Amazon Web Services AWS software | 17 |
| Spreadsheet software | 16 |
| Operating system software | 16 |
| Bash | 16 |
| Verilog | 15 |
| Splunk Enterprise | 15 |
| Salesforce software | 15 |
| MySQL | 15 |
| Ruby | 14 |
| StataCorp Stata | 14 |
| MathWorks Simulink | 14 |
| Graphics software | 14 |
| GitHub | 14 |
| Apache Hadoop | 14 |
| Microsoft Visual Basic for Applications VBA | 13 |
| Microsoft Dynamics | 13 |
| Hypertext markup language HTML | 13 |
| Email software | 13 |
| Database software | 13 |
| Teradata Database | 12 |
| PHP | 12 |
| Go | 12 |
| Enterprise resource planning ERP software | 12 |
| Computer aided manufacturing CAM software | 12 |

| | |
|---|---|
| Maplesoft Maple | 11 |
| Insightful S-PLUS | 11 |
| Docker | 11 |
| Geographic information system GIS systems | 11 |
| Geographic information system GIS software | 11 |
| Debugging software | 11 |
| Ansible software | 11 |
| Simulation software | 10 |
| NoSQL | 10 |
| Microsoft Exchange | 10 |
| Microsoft Visual Basic Scripting Edition VBScript | 10 |
| Finite element method FEM software | 10 |
| Adobe Systems Adobe Illustrator | 10 |

*Table 14 Most frequent skills associated with jobs of cluster 5. Source: personal elaboration*

Cluster 5 is made of 82 occupations. The total Euclidean distance between each job and the cluster's centroid is 4.302,21. The average distance in this cluster is thus 52,47.
In total 2.104 distinct digital skills are connected to jobs in cluster 5, with 5.599 observations. Each job is on average related to about 68 skills.

Cluster 5 contains jobs that are related to each other by having a similar educational background. As a matter of fact, basically every profession that is listed there requires at least a bachelor's degree. Although, this is the only characteristic they have in common, since they all differ from each other in terms of tasks carried out.

The fact that only the educational background is a recognizable pattern of this cluster can be seen also in the skills list, which is composed of software with different purposes. There are though some subgroups among this list like programming languages such as "Python", "C++", and "Perl", statistical software for managing databases like "Structured query language SQL", "SAS", or "R", and of course the Microsoft office suite, which is the most frequent set of digital skills in almost every cluster.

*3.1.6 Cluster 6*

| Occupations |
| --- |
| Geothermal Production Managers |
| Biomass Power Plant Managers |
| Gambling Managers |
| Postmasters and Mail Superintendents |
| Spa Managers |
| Tax Preparers |
| Surveyors |
| Nanotechnology Engineering Technologists and Technicians |
| Automotive Engineering Technicians |
| Calibration Technologists and Technicians |
| Materials Scientists |
| Neuropsychologists |
| Clinical Neuropsychologists |
| Preschool Teachers, Except Special Education |
| Kindergarten Teachers, Except Special Education |
| Secondary School Teachers, Except Special and Career/Technical Education |
| Special Education Teachers, Middle School |
| Substitute Teachers, Short-Term |
| Tutors |
| Craft Artists |
| Athletes and Sports Competitors |
| Dancers |
| Music Directors and Composers |
| Musicians and Singers |
| Disc Jockeys, Except Radio |
| Poets, Lyricists and Creative Writers |
| Court Reporters and Simultaneous Captioners |
| Camera Operators, Television, Video, and Film |
| Chiropractors |
| Dentists, General |
| Oral and Maxillofacial Surgeons |
| Orthodontists |
| Prosthodontists |
| Optometrists |
| Physician Assistants |
| Podiatrists |
| Occupational Therapists |
| Physical Therapists |
| Radiation Therapists |
| Respiratory Therapists |

| |
|---|
| Speech-Language Pathologists |
| Music Therapists |
| Advanced Practice Psychiatric Nurses |
| Critical Care Nurses |
| Nurse Anesthetists |
| Nurse Midwives |
| Audiologists |
| Cardiologists |
| Dermatologists |
| Emergency Medicine Physicians |
| Family Medicine Physicians |
| General Internal Medicine Physicians |
| Neurologists |
| Obstetricians and Gynecologists |
| Pediatricians, General |
| Physicians, Pathologists |
| Psychiatrists |
| Radiologists |
| Allergists and Immunologists |
| Hospitalists |
| Urologists |
| Physical Medicine and Rehabilitation Physicians |
| Sports Medicine Physicians |
| Ophthalmologists, Except Pediatric |
| Orthopedic Surgeons, Except Pediatric |
| Pediatric Surgeons |
| Acupuncturists |
| Dental Hygienists |
| Naturopathic Physicians |
| Orthoptists |
| Cytotechnologists |
| Histotechnologists |
| Histology Technicians |
| Cardiovascular Technologists and Technicians |
| Diagnostic Medical Sonographers |
| Nuclear Medicine Technologists |
| Radiologic Technologists and Technicians |
| Magnetic Resonance Imaging Technologists |
| Medical Dosimetrists |
| Emergency Medical Technicians |
| Paramedics |
| Pharmacy Technicians |
| Psychiatric Technicians |

| |
|---|
| Surgical Technologists |
| Opticians, Dispensing |
| Hearing Aid Specialists |
| Surgical Assistants |
| Midwives |
| Personal Care Aides |
| Nursing Assistants |
| Orderlies |
| Psychiatric Aides |
| Physical Therapist Aides |
| Massage Therapists |
| Dental Assistants |
| Phlebotomists |
| Speech-Language Pathology Assistants |
| Endoscopy Technicians |
| Customs and Border Protection Officers |
| Gambling Surveillance Officers and Gambling Investigators |
| Security Guards |
| Crossing Guards and Flaggers |
| Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers |
| Transportation Security Screeners |
| School Bus Monitors |
| Chefs and Head Cooks |
| Cooks, Fast Food |
| Cooks, Institution and Cafeteria |
| Cooks, Private Household |
| Cooks, Restaurant |
| Cooks, Short Order |
| Food Preparation Workers |
| Bartenders |
| Fast Food and Counter Workers |
| Baristas |
| Waiters and Waitresses |
| Food Servers, Nonrestaurant |
| Dining Room and Cafeteria Attendants and Bartender Helpers |
| Dishwashers |
| Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop |
| First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers |
| Janitors and Cleaners, Except Maids and Housekeeping Cleaners |
| Maids and Housekeeping Cleaners |
| Pest Control Workers |
| Landscaping and Groundskeeping Workers |
| Pesticide Handlers, Sprayers, and Applicators, Vegetation |

| |
|---|
| Tree Trimmers and Pruners |
| First-Line Supervisors of Entertainment and Recreation Workers, Except Gambling Services |
| First-Line Supervisors of Personal Service Workers |
| Gambling Dealers |
| Gambling and Sports Book Writers and Runners |
| Ushers, Lobby Attendants, and Ticket Takers |
| Amusement and Recreation Attendants |
| Costume Attendants |
| Locker Room, Coatroom, and Dressing Room Attendants |
| Embalmers |
| Crematory Operators |
| Funeral Attendants |
| Morticians, Undertakers, and Funeral Arrangers |
| Barbers |
| Hairdressers, Hairstylists, and Cosmetologists |
| Makeup Artists, Theatrical and Performance |
| Manicurists and Pedicurists |
| Shampooers |
| Skincare Specialists |
| Baggage Porters and Bellhops |
| Childcare Workers |
| Nannies |
| Cashiers |
| Gambling Change Persons and Booth Cashiers |
| Models |
| Telemarketers |
| Door-to-Door Sales Workers, News and Street Vendors, and Related Workers |
| Gambling Cage Workers |
| Hotel, Motel, and Resort Desk Clerks |
| Couriers and Messengers |
| Postal Service Clerks |
| Postal Service Mail Carriers |
| Postal Service Mail Sorters, Processors, and Processing Machine Operators |
| Agricultural Equipment Operators |
| Farmworkers and Laborers, Crop, Nursery, and Greenhouse |
| Farmworkers, Farm, Ranch, and Aquacultural Animals |
| Fishing and Hunting Workers |
| Fallers |
| Logging Equipment Operators |
| Boilermakers |
| Brickmasons and Blockmasons |
| Stonemasons |
| Carpenters |

| |
|---|
| Carpet Installers |
| Floor Layers, Except Carpet, Wood, and Hard Tiles |
| Floor Sanders and Finishers |
| Tile and Stone Setters |
| Cement Masons and Concrete Finishers |
| Terrazzo Workers and Finishers |
| Construction Laborers |
| Paving, Surfacing, and Tamping Equipment Operators |
| Pile Driver Operators |
| Operating Engineers and Other Construction Equipment Operators |
| Drywall and Ceiling Tile Installers |
| Tapers |
| Glaziers |
| Insulation Workers, Floor, Ceiling, and Wall |
| Insulation Workers, Mechanical |
| Painters, Construction and Maintenance |
| Paperhangers |
| Pipelayers |
| Plumbers, Pipefitters, and Steamfitters |
| Plasterers and Stucco Masons |
| Reinforcing Iron and Rebar Workers |
| Roofers |
| Sheet Metal Workers |
| Structural Iron and Steel Workers |
| Solar Photovoltaic Installers |
| Helpers--Electricians |
| Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons |
| Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters |
| Helpers--Roofers |
| Elevator and Escalator Installers and Repairers |
| Fence Erectors |
| Rail-Track Laying and Maintenance Equipment Operators |
| Septic Tank Servicers and Sewer Pipe Cleaners |
| Segmental Pavers |
| Derrick Operators, Oil and Gas |
| Rotary Drill Operators, Oil and Gas |
| Service Unit Operators, Oil and Gas |
| Earth Drillers, Except Oil and Gas |
| Explosives Workers, Ordnance Handling Experts, and Blasters |
| Continuous Mining Machine Operators |
| Roof Bolters, Mining |
| Loading and Moving Machine Operators, Underground Mining |
| Rock Splitters, Quarry |

| |
|---|
| Helpers--Extraction Workers |
| Radio, Cellular, and Tower Equipment Installers and Repairers |
| Telecommunications Equipment Installers and Repairers, Except Line Installers |
| Electrical and Electronics Installers and Repairers, Transportation Equipment |
| Electrical and Electronics Repairers, Commercial and Industrial Equipment |
| Electrical and Electronics Repairers, Powerhouse, Substation, and Relay |
| Electronic Equipment Installers and Repairers, Motor Vehicles |
| Audiovisual Equipment Installers and Repairers |
| Automotive Body and Related Repairers |
| Automotive Glass Installers and Repairers |
| Automotive Service Technicians and Mechanics |
| Bus and Truck Mechanics and Diesel Engine Specialists |
| Farm Equipment Mechanics and Service Technicians |
| Mobile Heavy Equipment Mechanics, Except Engines |
| Rail Car Repairers |
| Motorboat Mechanics and Service Technicians |
| Motorcycle Mechanics |
| Outdoor Power Equipment and Other Small Engine Mechanics |
| Bicycle Repairers |
| Recreational Vehicle Service Technicians |
| Tire Repairers and Changers |
| Mechanical Door Repairers |
| Home Appliance Repairers |
| Millwrights |
| Refractory Materials Repairers, Except Brickmasons |
| Electrical Power-Line Installers and Repairers |
| Telecommunications Line Installers and Repairers |
| Camera and Photographic Equipment Repairers |
| Musical Instrument Repairers and Tuners |
| Watch and Clock Repairers |
| Coin, Vending, and Amusement Machine Servicers and Repairers |
| Commercial Divers |
| Locksmiths and Safe Repairers |
| Manufactured Building and Mobile Home Installers |
| Riggers |
| Signal and Track Switch Repairers |
| Geothermal Technicians |
| Aircraft Structure, Surfaces, Rigging, and Systems Assemblers |
| Coil Winders, Tapers, and Finishers |
| Electrical and Electronic Equipment Assemblers |
| Electromechanical Equipment Assemblers |
| Engine and Other Machine Assemblers |
| Structural Metal Fabricators and Fitters |

| |
|---|
| Fiberglass Laminators and Fabricators |
| Timing Device Assemblers and Adjusters |
| Bakers |
| Butchers and Meat Cutters |
| Meat, Poultry, and Fish Cutters and Trimmers |
| Slaughterers and Meat Packers |
| Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders |
| Food Batchmakers |
| Food Cooking Machine Operators and Tenders |
| Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic |
| Forging Machine Setters, Operators, and Tenders, Metal and Plastic |
| Rolling Machine Setters, Operators, and Tenders, Metal and Plastic |
| Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic |
| Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic |
| Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic |
| Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic |
| Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic |
| Metal-Refining Furnace Operators and Tenders |
| Pourers and Casters, Metal |
| Model Makers, Metal and Plastic |
| Patternmakers, Metal and Plastic |
| Foundry Mold and Coremakers |
| Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic |
| Welders, Cutters, Solderers, and Brazers |
| Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic |
| Layout Workers, Metal and Plastic |
| Plating Machine Setters, Operators, and Tenders, Metal and Plastic |
| Tool Grinders, Filers, and Sharpeners |
| Print Binding and Finishing Workers |
| Laundry and Dry-Cleaning Workers |
| Pressers, Textile, Garment, and Related Materials |
| Sewing Machine Operators |
| Shoe and Leather Workers and Repairers |
| Shoe Machine Operators and Tenders |
| Sewers, Hand |
| Tailors, Dressmakers, and Custom Sewers |
| Textile Bleaching and Dyeing Machine Operators and Tenders |
| Textile Cutting Machine Setters, Operators, and Tenders |
| Textile Knitting and Weaving Machine Setters, Operators, and Tenders |
| Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders |
| Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers |
| Fabric and Apparel Patternmakers |
| Upholsterers |

| |
|---|
| Cabinetmakers and Bench Carpenters |
| Furniture Finishers |
| Model Makers, Wood |
| Patternmakers, Wood |
| Sawing Machine Setters, Operators, and Tenders, Wood |
| Nuclear Power Reactor Operators |
| Biomass Plant Technicians |
| Hydroelectric Plant Technicians |
| Chemical Plant and System Operators |
| Gas Plant Operators |
| Petroleum Pump System Operators, Refinery Operators, and Gaugers |
| Biofuels Processing Technicians |
| Chemical Equipment Operators and Tenders |
| Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders |
| Grinding and Polishing Workers, Hand |
| Cutters and Trimmers, Hand |
| Cutting and Slicing Machine Setters, Operators, and Tenders |
| Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders |
| Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders |
| Jewelers and Precious Stone and Metal Workers |
| Gem and Diamond Workers |
| Medical Appliance Technicians |
| Ophthalmic Laboratory Technicians |
| Painting, Coating, and Decorating Workers |
| Coating, Painting, and Spraying Machine Setters, Operators, and Tenders |
| Semiconductor Processing Technicians |
| Adhesive Bonding Machine Operators and Tenders |
| Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders |
| Cooling and Freezing Equipment Operators and Tenders |
| Etchers and Engravers |
| Molders, Shapers, and Casters, Except Metal and Plastic |
| Stone Cutters and Carvers, Manufacturing |
| Glass Blowers, Molders, Benders, and Finishers |
| Potters, Manufacturing |
| Paper Goods Machine Setters, Operators, and Tenders |
| Aircraft Cargo Handling Supervisors |
| Airline Pilots, Copilots, and Flight Engineers |
| Commercial Pilots |
| Flight Attendants |
| Ambulance Drivers and Attendants, Except Emergency Medical Technicians |
| Driver/Sales Workers |
| Heavy and Tractor-Trailer Truck Drivers |
| Light Truck Drivers |

| |
|---|
| Bus Drivers, School |
| Bus Drivers, Transit and Intercity |
| Shuttle Drivers and Chauffeurs |
| Taxi Drivers |
| Locomotive Engineers |
| Rail Yard Engineers, Dinkey Operators, and Hostlers |
| Railroad Brake, Signal, and Switch Operators and Locomotive Firers |
| Railroad Conductors and Yardmasters |
| Subway and Streetcar Operators |
| Captains, Mates, and Pilots of Water Vessels |
| Motorboat Operators |
| Bridge and Lock Tenders |
| Parking Attendants |
| Automotive and Watercraft Service Attendants |
| Aircraft Service Attendants |
| Transportation Inspectors |
| Passenger Attendants |
| Conveyor Operators and Tenders |
| Crane and Tower Operators |
| Dredge Operators |
| Hoist and Winch Operators |
| Industrial Truck and Tractor Operators |
| Cleaners of Vehicles and Equipment |
| Laborers and Freight, Stock, and Material Movers, Hand |
| Recycling and Reclamation Workers |
| Machine Feeders and Offbearers |
| Packers and Packagers, Hand |
| Gas Compressor and Gas Pumping Station Operators |
| Pump Operators, Except Wellhead Pumpers |
| Wellhead Pumpers |
| Refuse and Recyclable Material Collectors |
| Tank Car, Truck, and Ship Loaders |

*Table 15 List of jobs that are part of cluster 6. Source: personal elaboration*

| Digital skills | Frequency |
|---|---|
| Microsoft Excel | 307 |
| Microsoft Office software | 264 |
| Microsoft Word | 249 |
| Microsoft Outlook | 151 |
| Web browser software | 95 |
| Microsoft PowerPoint | 91 |

| | |
|---|---|
| Email software | 73 |
| Microsoft Windows | 65 |
| Word processing software | 45 |
| SAP software | 44 |
| Facebook | 44 |
| MEDITECH software | 37 |
| Autodesk AutoCAD | 34 |
| Spreadsheet software | 29 |
| Inventory tracking software | 29 |
| eClinicalWorks EHR software | 28 |
| Database software | 23 |
| Scheduling software | 21 |
| Intuit QuickBooks | 19 |
| Epic Systems | 19 |
| Point of sale POS software | 18 |
| Computer aided design CAD software | 18 |
| Electronic medical record EMR software | 18 |
| YouTube | 16 |
| Computerized maintenance management system CMMS | 14 |
| Microsoft Access | 13 |
| Global positioning system GPS software | 13 |
| Bizmatics PrognoCIS EMR | 13 |
| Enterprise resource planning ERP software | 12 |
| Adobe Systems Adobe Photoshop | 12 |
| GE Healthcare Centricity EMR | 11 |
| Turtle Creek Software Goldenseal | 10 |
| Practice management software PMS | 10 |
| Medical procedure coding software | 10 |
| Greenway Medical Technologies PrimeSUITE | 10 |
| Inventory control software | 10 |
| Inventory management systems | 10 |
| Supervisory control and data acquisition SCADA software | 9 |
| GalacTek ECLIPSE | 9 |
| Corel WordPerfect Office Suite | 9 |
| Appointment scheduling software | 9 |
| Adobe Systems Adobe Illustrator | 9 |
| simplifyMD | 8 |

*Table 16 Most frequent skills associated with jobs of cluster 6. Source: personal elaboration*

Cluster 6 is the largest cluster by size, as it contains 373 occupations. Total distance within the cluster is 3.753,82 and the average distance is the lowest among all clusters, with 10,06.

The occupations of this cluster are associated with 1.785 skills, whose total observations equal 4.553. Therefore, each job is related on average to 12 digital skills.

This cluster includes many different and apparently unrelated occupations. Many of the jobs listed in Table 16 are blue-collar jobs that have little or no educational requirements. There are though some occupations that require an undergraduate or even graduate degree as for example “Materials Scientists”, “Clinical Neuropsychologists”, or “Physical Therapists”.

Despite containing jobs that seem highly unrelated, cluster 5 has the lowest average distance, meaning that these jobs are in fact strongly related on the basis of the digital skills they are associated with. This peculiarity could seem to be a paradox, but it can be explained by the fact that these professions are similar because they don’t involve using many digital skills. As a matter of fact, cluster 5 is also the cluster with the lowest skills observation on size ratio as mentioned before.

### *3.1.7 Cluster 7*

| Occupations |
|---|
| Computer and Information Systems Managers |
| Management Analysts |
| Computer Systems Analysts |
| Information Security Analysts |
| Computer User Support Specialists |
| Computer Network Architects |
| Database Administrators |
| Database Architects |
| Data Warehousing Specialists |
| Network and Computer Systems Administrators |
| Computer Programmers |
| Software Developers |
| Software Quality Assurance Analysts and Testers |
| Web Developers |
| Web and Digital Interface Designers |
| Computer Systems Engineers/Architects |
| Information Technology Project Managers |
| Business Intelligence Analysts |

*Table 17 List of jobs that are part of cluster 7. Source: personal elaboration*

| Digital skills | Frequency |
|---|---|
| Splunk Enterprise | 18 |
| UNIX | 18 |
| Tableau | 18 |
| Python | 18 |
| SAP software | 18 |
| Qlik Tech QlikView | 18 |
| Structured query language SQL | 18 |
| Red Hat Enterprise Linux | 18 |
| Teradata Database | 18 |
| Relational database management software | 18 |
| Ruby on Rails | 18 |
| Shell script | 18 |
| MicroStrategy | 18 |
| Oracle Fusion Applications | 18 |
| PostgreSQL | 18 |
| Microsoft .NET Framework | 18 |
| Oracle WebLogic Server | 18 |

| | |
|---|---|
| Microsoft Access | 18 |
| MySQL | 18 |
| Microsoft Azure software | 18 |
| Oracle Business Intelligence Enterprise Edition | 18 |
| Microsoft Dynamics | 18 |
| Oracle PL/SQL | 18 |
| Microsoft Excel | 18 |
| Microsoft Visual Studio | 18 |
| Microsoft Office software | 18 |
| MongoDB | 18 |
| Microsoft Project | 18 |
| Nagios | 18 |
| Microsoft SharePoint | 18 |
| NoSQL | 18 |
| Microsoft SQL Server | 18 |
| Oracle Database | 18 |
| Microsoft SQL Server Reporting Services SSRS | 18 |
| Oracle Java | 18 |
| Microsoft Visio | 18 |
| Oracle Solaris | 18 |
| Microsoft Visual Basic | 18 |
| Microsoft Visual Basic Scripting Edition VBScript | 18 |
| Perl | 18 |
| Integrated development environment IDE software | 18 |
| IBM Domino | 18 |
| IBM Cognos Impromptu | 18 |
| Eclipse IDE | 18 |
| IBM WebSphere | 18 |
| Extensible markup language XML | 18 |
| KornShell | 18 |
| Hewlett Packard HP-UX | 18 |
| Linux | 18 |
| Atlassian JIRA | 18 |
| Common business-oriented language COBOL | 18 |
| C# | 18 |
| Advanced business application programming ABAP | 18 |
| Apache Solr | 18 |
| Amazon Web Services AWS software | 18 |
| C | 18 |
| Apache Cassandra | 18 |
| C++ | 18 |
| Apache Hadoop | 18 |
| Customer information control system CICS | 18 |
| Apache HTTP Server | 18 |
| Apache Pig | 18 |

| | |
|---|---|
| Ubuntu | 17 |
| SAS | 17 |
| Unified modeling language UML | 17 |
| Red Hat WildFly | 17 |
| SAP Crystal Reports | 17 |
| The MathWorks MATLAB | 17 |
| Microsoft Active Server Pages ASP | 17 |
| Perforce Helix software | 17 |
| Oracle JD Edwards EnterpriseOne | 17 |
| NortonLifeLock cybersecurity software | 17 |
| PHP | 17 |
| JavaScript | 17 |
| IBM Power Systems software | 17 |
| IBM InfoSphere DataStage | 17 |
| Extensible hypertext markup language XHTML | 17 |
| Enterprise JavaBeans | 17 |
| Drupal | 17 |
| Hypertext markup language HTML | 17 |
| Job control language JCL | 17 |
| Amazon Redshift | 17 |
| Bash | 17 |
| Apache Tomcat | 17 |
| Apache Hive | 17 |
| Apache Kafka | 17 |
| CA Erwin Data Modeler | 17 |
| Wireshark | 16 |
| UNIX Shell | 16 |
| Ruby | 16 |
| Transact-SQL | 16 |
| Veritas NetBackup | 16 |
| Swift | 16 |
| SAP Business Objects | 16 |
| Puppet | 16 |
| Oracle JavaServer Pages JSP | 16 |
| Oracle PeopleSoft | 16 |
| Oracle JDBC | 16 |
| McAfee | 16 |
| Node.js | 16 |
| Microsoft PowerShell | 16 |
| Microsoft SQL Server Integration Services SSIS | 16 |
| Microsoft ASP.NET | 16 |
| Oracle Hyperion | 16 |
| Microsoft PowerPoint | 16 |
| Microsoft Windows | 16 |
| Microsoft Windows Server | 16 |

| | |
|---|---|
| NetSuite ERP | 16 |
| JavaScript Object Notation JSON | 16 |
| IBM Notes | 16 |
| Git | 16 |
| GitHub | 16 |
| Elasticsearch | 16 |
| Dynamic hypertext markup language DHTML | 16 |
| ESRI ArcGIS software | 16 |
| Amazon Elastic Compute Cloud EC2 | 16 |
| Apache Maven | 16 |
| Atlassian Confluence | 16 |
| Apache Ant | 16 |
| AJAX | 16 |
| Apache Subversion SVN | 16 |
| Apache Groovy | 16 |
| Apache Spark | 16 |
| Apache Struts | 16 |
| Apple macOS | 16 |
| Spring Framework | 15 |
| Virtual private networking VPN software | 15 |
| Scala | 15 |
| VMware | 15 |
| Oracle E-Business Suite Financials | 15 |
| Microsoft ActiveX | 15 |
| Oracle Fusion Middleware | 15 |
| Microsoft Visual Basic for Applications VBA | 15 |
| Microsoft Exchange | 15 |
| Django | 15 |
| LAMP Stack | 15 |
| Hibernate ORM | 15 |
| Go | 15 |
| jQuery | 15 |
| FileMaker Pro | 15 |
| Hewlett Packard LoadRunner | 15 |
| Citrix cloud computing software | 15 |
| Chef | 15 |
| Amazon DynamoDB | 15 |
| Atlassian Bamboo | 15 |
| Ansible software | 15 |
| StataCorp Stata | 14 |
| R | 14 |
| Microsoft Publisher | 14 |
| Microsoft ASP.NET Core MVC | 14 |
| Microsoft Word | 14 |
| IBM SPSS Statistics | 14 |

| | |
|---|---|
| Docker | 14 |
| Google Angular | 14 |
| Ext JS | 14 |
| Human resource management software HRMS | 14 |
| Adobe Systems Adobe Dreamweaver | 14 |
| Delphi Technology | 14 |
| Adobe Systems Adobe ActionScript | 14 |
| Salesforce software | 13 |
| Skype | 13 |
| Red Hat OpenShift | 13 |
| Selenium | 13 |
| Microsoft Dynamics GP | 13 |
| Jupyter Notebook | 13 |
| JUnit | 13 |
| Epic Systems | 13 |
| Geographic information system GIS software | 13 |
| Google Analytics | 13 |
| Cisco Webex | 13 |
| Blackboard software | 13 |
| Amazon Simple Storage Service S3 | 13 |
| Adobe Systems Adobe Acrobat | 13 |
| Cascading style sheets CSS | 13 |
| Spring Boot | 12 |
| Salesforce Visualforce | 12 |
| Oracle Eloqua | 12 |
| Microsoft Outlook | 12 |
| Objective C | 12 |
| Oracle Primavera Enterprise Project Portfolio Management | 12 |
| Amazon Web Services AWS CloudFormation | 12 |
| Adobe Systems Adobe Fireworks | 12 |
| Backbone.js | 12 |
| Supervisory control and data acquisition SCADA software | 11 |
| Minitab | 11 |
| Oracle PeopleSoft Financials | 11 |
| LexisNexis | 11 |
| Blackbaud The Raiser's Edge | 11 |
| 3M Post-it App | 11 |
| Google Docs | 10 |
| React | 9 |

*Table 18 Most frequent skills associated with jobs of cluster 7. Source: personal elaboration*

The last cluster includes only 18 occupations, making it the smallest cluster in terms of size. The total distance within the cluster is 1.846,05 and the distance mean is thus 102,56, which is the highest average distance among all seven clusters.
There are 1.112 distinct skills associated with the jobs that belong to this group. Total observations of these skills is 4.921, which means that each profession is on average connected to more than 273 digital skills.

The jobs that are part of cluster number 7 have in common the fact that they're all part of the Information Technology (IT) industry, except for "Management Analysts", which is a consultancy job that consists of recommending ways to improve an organization's efficiency. The fact that basically every job in that list is in the high-tech sector is evident also by looking at Table 18. This can be seen from two different perspectives. First, by looking at the number of skills that compose the list; cluster 7 is in fact the class of occupations with the highest average number of digital skills per job and thus it can be regarded as the most digital cluster. Second, by analyzing the type of skills that are included in Table 18; the vast majority of them as well as the most frequent ones are mostly programming languages and data analysis software.

It is remarkable how basic and general-purpose software like "Email Software", "Microsoft Word", and "Web browser software", are not among the most frequent skills. This can be considered as a further demonstration of the fact that these skills are not associated with many high-tech occupations because most employers might give them for granted and they don't include them in the job postings. For this reason, they don't end up in the data gathered by O*Net's occupational analysts.

### *3.1.8 General considerations on k-means cluster partition*

At the digital skills level, the most remarkable thing to highlight in the *k*-means cluster analysis is the fact that for most clusters Microsoft Office suite is among the most frequent skills. This is arguably a predictable result, since the software included in Microsoft Office are also the most frequent skills in general according to Table 2. It is though still important to highlight this as it shows how it is essential nowadays to possess this set of competencies as they're required for most occupations.

When analyzing the clusters by looking at both the occupations and the Euclidean distances, a peculiar relationship comes up. Cluster 2 and Cluster 6 have respectively the third and the first lowest average distance, meaning that the jobs that are in those groups are deeply similar by digital skills involved. However, those professions are also very diverse in terms of tasks carried out and industries of operation.

At the same time, the other clusters seem to follow a pattern in terms of tasks and industry similarity, but, except for cluster number 4, they all have a distance mean higher than cluster 2 and cluster 6's ones, meaning that they're less similar then the other two clusters in terms of digital skills.

This peculiarity can be explained by the fact that cluster 2 and cluster 6, along with cluster 4, have the lowest number of skills per job, respectively 31, 12, and 32. Therefore, their lower average Euclidean distance might be explained by the fact that having few skills implies as well having a small distance from the cluster's centroid.

The number of skills per job of each cluster is significant also for giving an idea on which clusters are more digital than others, with cluster 7 being by far the most digital of all clusters (273 skills per job) and cluster 6 the least digital (12 skills per job).

In order to make those classes easier to be identified, as well as the following analysis easier to be read, clusters have been renamed according to the most prominent trait that the jobs they include have in common. Only cluster 2 could not be categorized due to the fact its occupations are too many and variegated. As a result of that, its name was not changed.

These are the new names that will be used in the remaining part of this thesis.

- Cluster 1 → Creative workers
- Cluster 2 → Cluster 2
- Cluster 3 → Administration and finance

- Cluster 4 → Teachers and professors
- Cluster 5 → Professionals
- Cluster 6 → Manual laborers
- Cluster 7 → Programmers and system administrators

## 3.2 Principal Component Analysis

The statistical analysis carried out following the *k*-means clustering is the Principal Component Analysis (PCA). This analysis was implemented to serve two purposes for the thesis. The first one was to provide a visual representation of the clusters obtained through the *k*-means analysis, while the second purpose was to look at the jobs-digital skills relationship from a different perspective.

The PCA is a linear dimensionality reduction technique that linearly transforms data into a new coordinate system so that the directions, which are called principal components, that capture the largest variation in the data can be easily identified.
This analysis was conducted using RStudio. The software calculated the variance using the binary matrix that was created for the *k*-means clustering.

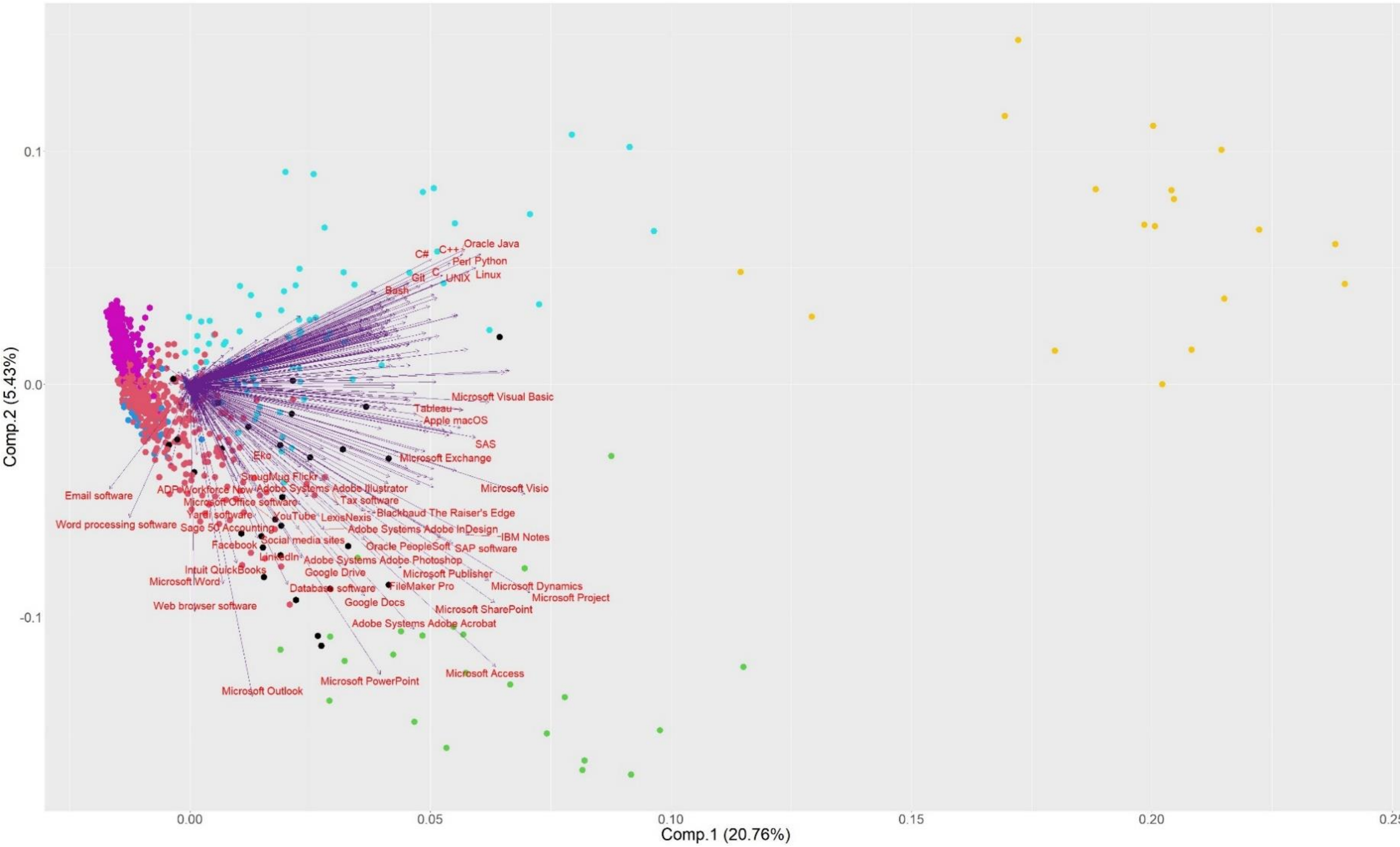


*Figure 5 PCA graphical representation. Source: personal elaboration*

Figure 4 shows the graphical representation resulting from the PCA conducted using RStudio. The axis "Comp.1" and "Comp.2" represent the two linear combinations that RStudio found that maximize the variance for this dataset; the percentages in brackets show how much variation each linear combination illustrates on total.

Every dot on the graph indicates an occupation and they are colored differently according to the cluster they belong to. Therefore, there are in total six different colors, each one indicating a different group and they are associated as follows:

- Creative workers → Black

- Cluster 2 → Red
- Administration and finance→ Green
- Teachers and professors → Blue
- Professionals → Cyan
- Manual laborers → Purple
- Programmers and system administrators → Yellow

Dots are positioned on the graph according to which skills they depend on.
Arrows start from the graph's center which has coordinates (0;0). The more distant the points are from the center, the more dependent they are to one or more specific skills and less on the others. On the other hand, those dots that are close to the center of the graph are either dependent on multiple skills in similar measure or they are slightly dependent to very few of them.
The arrows represent digital skills. As for the points, each arrow stands for a distinct digital skill and they different length and direction. The length of an arrow indicates how strong the dependency between that skill and the jobs in that direction is.
Some arrows also have a label that specifies what skill they represent. These labels were added using RStudio and only a few of the skills have them. That's because adding them to all the competencies would have meant having a chaotic and unreadable graph. The algorithm itself decided which arrows to label and which not; it chose to label the ones it considered to be the most relevant.

The most remarkable thing about the PCA's outcomes is that they're consistent with the results from the former analysis. As a matter of fact, occupations from the same cluster are distributed close to each other. This happens for all the clusters except for creative workers, that are scattered around the graph, but still in a quite restricted area.

Differences between clusters in terms of average distance can be seen in this analysis. In fact, cluster 2, teacher and professors, and manual laborers all had a much lower mean distance than other clusters and they are much more concentrated than the others.

Those same three clusters are positioned in proximity of the graph's center. That's because the jobs that compose them require on average few digital skills.
For the opposite reason, the other clusters are all further away from the center as their occupation are associated on average with more digital skills. Therefore, administration and finance as well as programmers and system administrators are the two classes of jobs that are the furthest from the center as they are respectively the second and the first cluster by number of average digital skills.

The arrows are extremely indicative of the most important skills for each cluster. Both professionals and programmers and system administrators have in fact "C++", "Oracle Java", and the other labelled arrows pointing at the top-right corner of the graph among their most frequent skills. The same happens for creative workers, administration and finance, as well as some jobs that are part of cluster 2 since they have those digital skills pointing at them in the graph as the most frequent ones.

## 3.3 Support Vector Machine Analysis

Following the PCA, another cluster analysis was implemented using Support Vector Machine (SVM) on RStudio. SVM is a machine learning model that groups data into two clusters.
The SVM algorithm classified all jobs based on differences in digital skills using the same binary matrix that was introduced for the *k*-means analysis and which was utilized for the PCA too. In order to provide a visual representation of the results from this analysis, the PCA was implemented again for this part.

Since the SVM creates only two clusters, a *k*-means analysis with *k*=2 was computed too, in order to compare the results. For convenience reasons, only the graphical representation of both analyses is here provided.

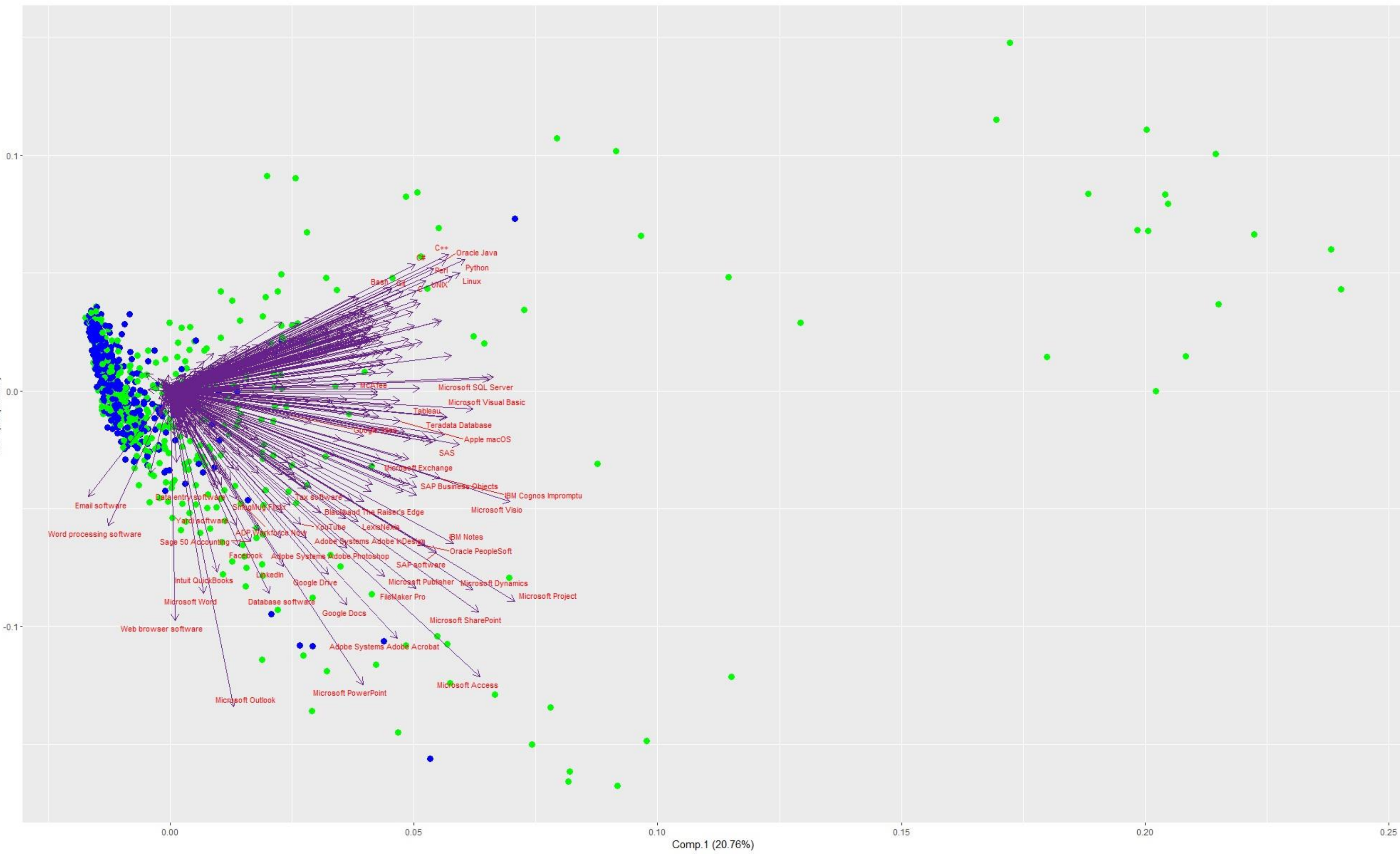


*Figure 6  SVM graphical representation. Source: personal elaboration*

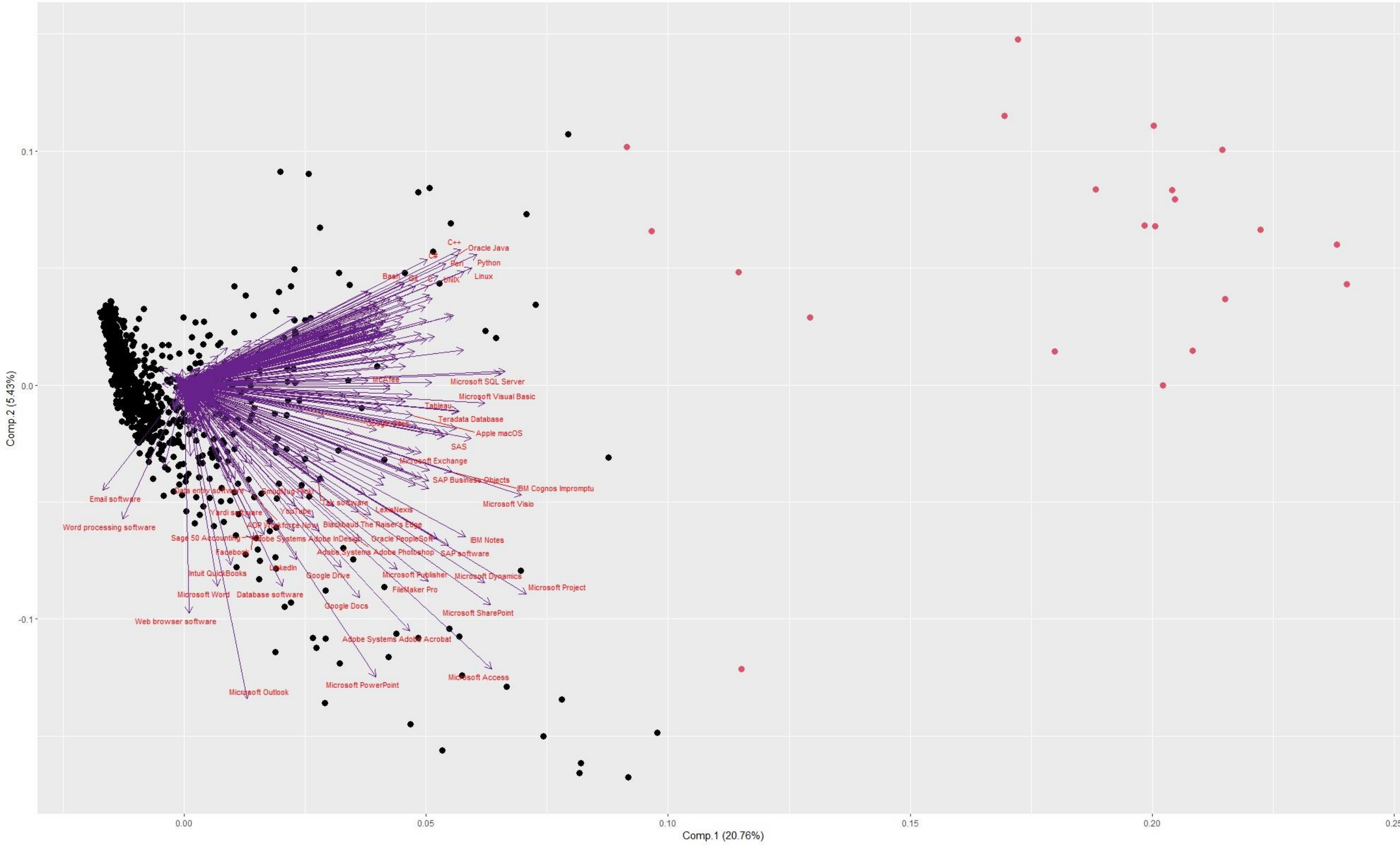


*Figure 7 k-means, k=2 graphical representation. Source: personal elaboration*

The two graphs show completely different outcomes as expected, given that the two algorithms use different functions to classify data into classes.

The SVM analysis, apart from some errors that can be spotted, seems to group most of the jobs that are concentrated in that dense cloud of dots left to the graph's center. Therefore, it looks like SVM puts together occupations that in the previous cluster analysis were in the groups of cluster 2, creative workers, and manual laborers.

*k*-means analysis with *k*=2 on the other hand creates two more imbalanced clusters in terms of number of components. In fact, the smaller cluster, whose jobs are indicated with red dots in Figure 6, includes only professions that are in the programmers and system administrator’s class, along with two jobs from the professionals’ cluster and one from the administration and finance.

Both the clusters seem to separate digital jobs from non-digital ones. However, it is interesting to notice how they do it. By dividing professions that are left to the center of the graph from the remaining ones, the SVM clustering appears to separate occupations that involve a minimum use of digital skills from jobs that require none or very few of them. On the other hand, the *k*-means algorithm seems to split those professions that are placed in the top right corner of the graph from the rest, meaning that for this other algorithm digital jobs are only those occupations associated with an incredibly high number of digital skills, while all the others are regarded as non-digital.

## 3.4 From the digital skills to the clusters

The last analysis carried out for this thesis consisted of looking at the jobs-digital skills relationship from the opposite perspective. So far, all the analyses implied looking first at the occupations to see which digital skills they’re associated with. Conversely, this other analysis has digital skills as a starting point. In fact, given any set of digital skills from the O*Net database it shows what cluster of jobs it’s associated with.

This analysis was calculated with the use of RStudio. It requires first the *k*-means clustering model launched and the binary matrix it’s based on created. The algorithm uses the predict function for *k*-means (pred_kmeans) to connect a dataset of skills to its cluster. The dataset with all the chosen digital skills must be created manually on an Excel sheet, which must be linked to the RStudio file. In the Excel sheet  the list of skill must be included in a table.


*Figure 8  Screenshot of RStudio's console with a result from the algorithm.*

In order to predict the cluster, the algorithm first creates a new job using all the skills that were given as input and calculates its coordinates. It then computes the Euclidean distances from all of the clusters' centers and eventually picks the closest one.

For this thesis, several attempts were made with different datasets to test the algorithm. Datasets differed both in size and in the type of skills included. The latter were chosen randomly.

Most of the attempts gave cluster 6 as a result, which is the manual laborers' cluster. This was true especially with fewer skills. The reason behind this has to be traced to the fact that manual laborers is the cluster with the fewest average skills per job.

Since digital technologies have been developing so fast in the last few years, the job market has changed a lot; new jobs have sprung and many more will in the future, as well as new digital skills will be required by employers to both incumbents and prospective employees (Colombo et al, 2019). Hence, this simple predictive algorithm was conceived also as a tool to use for those new digital jobs that lack of job description or that have a very concise one, so that someone can get to know what kind occupations a job is similar to on the basis of the digital skills that are required for that distinct job.

# CONCLUSIONS

This thesis allowed to take a better look at the relationship between occupations and digital skills. The descriptive analyses in chapter two showed that a decent level of digital literacy is required by most jobs in today's labor market. As a matter of fact, the analyses in the second chapter demonstrated that most occupations involve knowing how to use several different software. However, and this is the major flaw found in the O*Net database, it could not be possible to discover how often these skills are actually required when performing the job. The only related piece of information which could be gathered is whether a specific skill is usually required in jobs postings or not.
It was opted for not including the hot technology column in the analysis, as it is believed that the same information could be extracted from the digital skills frequency tables.
Chapter two also showed which digital skills are the most common. The results didn't surprise much as at the top of the table can be found the Microsoft Office suite as well as other basic software. On the other hand, results were a bit more unexpected for what concerned professions with the most digital skills. In fact, several non-high-tech jobs are associated with many digital skills, sometimes even more than typical IT occupations.
It is important to highlight that some data found in the made database little sense. This is the case among others of the "Microsoft Windows", which is associated both to high-tech and non-high-tech professions. Thus, it's not clear whether that skill simply means being able to run a computer or being able to work with the operating system's architecture.

Chapter three investigated the jobs similarities in terms of digital skills entailed. All of the three cluster analyses gave reasonable results. *K*-means analysis found seven classes of occupations very different in size and composition; besides cluster number 2, all the other groups showed some traits in common. It was interesting to note that the clusters with the lowest average Euclidean distance were the ones with the most miscellaneous professions as they happened to be the ones with the fewest digital skills as well.
PCA allowed to visualize the results as well as to look at the digital skills clusters are more dependent to, thanks to the arrows in the graph. It's important to stress that except for

creative workers' cluster, jobs that are part of all the other classes are distributed next to each other, meaning that PCA's outcomes are consistent with the ones from the *k*-means clustering.

The last type of cluster analysis undertaken, that is the SVM, divided professions into two groups. Based on the kind of clusters created, they were regarded as a division between lowly digitalized occupations and more digitalized ones. Whereas the *k*-means clustering with k=2, which was computed shortly after, separated very highly digitalized jobs from the remaining. This last analysis was carried out in order to compare its results with the ones obtained from the SVM, since they both consist of subdividing a set into two subgroups.

Eventually, it was created an algorithm that given a set of skills of an existent or hypothetical job it tells what cluster that profession would be part of. It was meant as a tool for looking at the occupations-digital skills relationship from the opposite perspective. Moreover, it could also be helpful in the case of a new occupation to find out given its requirements to what jobs it's the most similar.

As a prospective future development of this thesis, it would be useful to implement the last algorithm with a larger number of clusters in order to be more precise, especially in the case of few digital skills provided as input. Another possible development would be to calculate each cluster's average annual income, in order to investigate further the relationship between digitalization and wages.

## LINK TO THE TABLES

https://drive.google.com/drive/folders/1uM4Nyv57dsYAYXb47ntNpiaUr5tPyPPc?usp=sharing

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