Discussion paper

Digital score for occupations

Digital skills and competencies

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Summary

The consequences of digitalization for economic progress hold significant social and economic importance. The transformation driven by digitalization is largely mediated through the digital competencies of the labor force, a trend that is increasingly evident in the rapidly evolving labor market. For a successful digital economy, it is essential to cultivate new knowledge in digital technologies and promote the application of specialized digital skills. A key focus of our research is to understand how digital competencies influence labor market dynamics. Motivated by this, we conduct a study aimed at developing a digital indicator for occupations based on digital skills.

To explore the relationship between digital skills and occupations, we employ two data frameworks: European Skills, Competences, Qualifications and Occupations (ESCO)[1] and CompetentNL[2]. ESCO serves as a European multilingual classification system for skills, competences, qualifications, and occupations, while CompetentNL is a national standard used to describe skills in the context of vacancies, training, and education.

For both frameworks, we established a three-level classification of digital skills, based on the complexity of the required competencies. Using this classification, we propose a digital score indicator for occupations, which quantifies the level of digital literacy required in various professional roles. Subsequently, we focus on quantifying the labor force associated with digitally skilled occupations. This approach allows for the creation of aggregated tables that represent the distribution of the labor force across industry sectors, along with derived digital scores for each sector.

Keywords
Digital economy, Labor force, Digital skills, ESCO, CNL-UWV, ISCO, BRC.

[1] Digital Skills and Knowledge Concepts | ESCO
[2] CompetentNL

Content

1. **Introduction 4**

2. **The literature overview 5**
   2.1 Identifying digital skills 6

3. **Skill ontologies 8**
   3.1 European skills qualifications competencies and occupations (ESCO) 8
   3.2 CompetentNL and CNL-UWV 10
   3.3 CNL-UWV vs ESCO 11
   3.4 Classification ESCO and CNL-UWV occupations 12

4. **Digital skills and digital scores 13**
   4.1 CNL-UWV digital skills 13

   4.1.1 Relevance of digital terms in identifying digital skills 14

   4.1.2 Non-digital terms for digital skills 15
   4.2 Complexity of digital skills in CNL-UWV and ESCO 15
   4.3 Digital scores for occupations 17
   4.4 Digital scores for ISCO and BRC classifications 20

5. **Results 21**
   5.1 Digital skills and digital occupations in ESCO and CNL-UWV 21
   5.2 Aggregated digital scores 23
   5.3 Comparison of digital score and ISCO - level for ESCO and CNL-UWV data 25

6. **Discussion 26**
   Acknowledgments 28

   References 29

Appendix A 'ICT' occupations within CNL-UWV and Non-digital terms **30**

Appendix B Concordance coefficient **31**

Appendix C Calculating digital scores for different occupations from CNL-UWV **32**
'ICT system developers and analysts' 32
'Accountants' 33
'Firefighters' 34

Appendix D Different values of λ **35**

1. Introduction

In 2022, the Dutch labor market experienced a significant shortage, with staff shortages reported across various occupations and industries. According to Statistics Netherlands (SN), for every 100 job seekers, there were 127 vacancies reported—marking the highest number since the collection of such data began in 1971. This shortage is driven by multiple factors, including an aging population, a high proportion of part-time workers, and mismatches between the supply and demand of labor in terms of profession, education, skills, and geographic location. These discrepancies often prevent vacancies from being filled by unemployed individuals. The labor shortage is most pronounced in the Information and Communication sector, where digital skills and competencies are most in demand. This is followed by the Construction and Accommodation sectors, as well as Food Service activities.

The consequences of digitalization for economic progress are of crucial social and economic importance. Digitalization is reshaping the labor market, and its effects can be observed through the digital competencies of the labor force. This transformation is particularly evident in the rapidly evolving landscape of labor skills, which is not only driven by automation and repetitive tasks but also by the emergence of technologies such as Generative Artificial Intelligence (GenAI). For instance, it has been estimated that "approximately 79% of working women have positions susceptible to automation, versus 58% of working men"[3]. The introduction of Large Language Models is also beginning to influence or potentially replace certain occupations, as seen in the recent strike by the Writers Guild of America, who called for greater regulation of AI alongside higher wages and better residuals from streaming platforms.

Given these developments, it is essential to understand and monitor the changes that digitalization is bringing to the labor force, with a specific focus on identifying which digital skills are becoming increasingly essential. The goal of this paper is to develop a digital score indicator that can be used to assess the extent of digital skills in the Dutch labor market in the future. To achieve this, we investigate the relationships between digital skills and occupations using two data frameworks that provide detailed links between skills and occupations—referred to as skill ontologies. These frameworks are the European Skills, Competences, Qualifications and Occupations (ESCO)[4], and CompetentNL. ESCO is a European multilingual classification system for skills, competences, qualifications, and occupations, while CompetentNL is a national standard for describing skills in the context of vacancies, training, and education. A more detailed description of these skill ontologies is provided in Section 3.

[3] Will AI Replace Jobs? 17 Job Types That Might be Affected
[4] Digital Skills and Knowledge Concepts | ESCO

Note that there is a distinction between skills and tasks. A person requires certain skills in order to carry out specific tasks. A task is a specific kind of work assigned to be completed within a certain timeframe, and it often requires a variety of skills to be executed successfully. In this paper, we examine the connections between occupations and "skills." Here, "skills" are defined as a term encompassing knowledge areas and capabilities. Tasks are not included in our analysis.

The research approach of this paper is structured as follows: First, we compile a comprehensive list of digital skills. Based on the complexity of each skill, we define a three-level classification within both skill ontologies. Using this classification, we then define a digital score indicator for occupations. The digital scores derived from ESCO and CompetentNL data are aggregated at higher levels of the International Standard Classification of Occupations (ISCO)[5]. We also compare the results obtained from the two ontologies.

The paper is organized as follows: Section 2 provides a brief literature review of studies on digital skills and occupations, along with an exploration of the definitions of digital skills. Section 3 describes the framework and data sources of the skill ontologies used in this study. In Section 4, we define the digital skills and the digital score indicators. Section 5 presents the results of the digital indicators for occupations within the two data frameworks. Finally, Section 6 offers a discussion of the findings and their implications.

2. The literature overview

The research on skills and especially on digital skills using skill ontologies is new, however it is a rapidly growing research topic. We are interested in studies conducted for defining digital score for occupations. Defining digital skills and occupations is highly dependent on the available information on skills. The most used frameworks that link skills and occupations are ESCO, O*NET data, DBpedia, Stack Overflow and the European Skills Framework. Researchers also often use the vacancy texts to define which skills are required for certain occupations and map the required skills with the occupations.

In (Lennon, Zilian and Zilian 2022) the authors used the ESCO database to define a digitalization measure of occupations. They construct a set of Digital Competencies Indicators (DCI) per occupation inspired by network analysis methods and using Natural Language Processing (NLP) tools. The DCI is the ratio of the share of digital skills in an occupation to the share of digital skills in all occupations. Authors also give the results of digital occupations for the ISCO, what makes possible to apply the indicator in analyses on employment, earnings, and social exclusion. In another extended study (den Uijl, Kumar en Prüfer 2023) skills are collected from various

[5] https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

sources. One of the most important data sources in this research are online vacancies, from which skills are determined and occupations can be compared. To include skills required that are not mentioned in vacancy texts, other sources such as O*NET, DBpedia, Stack overflow and the European skills framework are also used. The skills are divided into digital skills and other skills. The general trend found in this research is that job requirements in the field of digitalization with regard to more complex digital skills are gradually increasing. This research also shows the change in demand for digital skills in vacancies between 2012 and 2021, for example the number of vacancies mentioning 'Programming skills' increased by 17%. Specifically, the trend of a significant increase in demand for digital transformation and big data & analytics is observed. The digitization aspects covered in this study include: research into the tasks, skills, and competencies that have become more important over time per occupation. The similarities between this and our research concern questions about skills that have been introduced by digitization and are becoming important to have.

Another highly relevant study conducted by Burning Glass Technologies and Bertelsmann Stiftung to understand and map the current trends of digitalization in the German labor market (O'Kane, et al. 2020). To do this, the authors defined a digitalization index per profession using vacancy data. This index allows analyses of the levels and changes in demand for digital skills in Germany over the period 2014-2018. The index scores each profession on the digital scale from 0 to 100. In addition to digitalization per profession, it is used for analysis to map digitalization by region, sector, education, gender, and salary. For Germany, job gains and losses are expected to occur. Automation will remain in balance until at least the middle of the next decade. However, the crucial condition for this is that the working population keeps pace with digitalization.

2.1 Identifying digital skills

Identifying whether a skill is digital requires a formal and consistent definition of digital skills. While it is generally accepted that developing software constitutes a digital skill, the scope of digital skills extends far beyond this. The digitization of the economy and society, which began with the advent of personal computers, the internet, smartphones, and more recently, AI applications, has transformed the nature of work and the skills required across industries.

The literature on digital skills reflects an ongoing debate regarding their scope. Some authors argue that digital skills should not be limited to Information and Communication Technologies (ICT) alone. According to (Ferrari 2012), digital skills encompass a wide range of competencies, including information management, collaboration, communication, content and knowledge creation, ethics and responsibility, evaluation and problem-solving, and technical actions. As digitalization continues to evolve, so does the concept of digital skills. The definition has changed significantly over the past decade and is expected to continue evolving in the future. This makes it increasingly important to develop robust tools and frameworks for describing and categorizing digital skills.

Several studies have attempted to define the skills necessary for a knowledge-based society in the context of the 21st century. (van Laar, et al. 2017) conducted a systematic literature review to investigate the relationship between 21st-century skills and digital skills. Their review highlighted a lack of consistency in terminology across different studies. The authors concluded that 21st-century digital skills go beyond the technical use of digital tools and include cognitive and socio-emotional competencies. Key terms used in the literature include digital competence, digital literacy, e-skills, 21st-century learning or thinking skills, and 21st-century competence.

In a study by (den Uijl, Kumar en Prüfer 2023), digital skills were categorized into 13 distinct categories, each with associated sub-skills. For example, the category "Digital transformation skills" includes techniques related to developments in digitization, such as 3D printing, artificial intelligence (AI), blockchain, cloud computing, cybersecurity, the Internet of Things, and robotics.

In this study, we adopt the definition of digital competence provided by the European Skills Classification, known as 'DigComp', which is based on the Council Recommendation on Key Competences for Lifelong Learning. According to this definition, digital competence involves the confident, critical, and responsible use of, and engagement with, digital technologies for learning, work, and social participation. It encompasses the following key areas:
- Information and data literacy,
- Communication and collaboration,
- Media literacy,
- Digital content creation (including programming),
- Safety (including digital well-being and cybersecurity),
- Intellectual property-related questions,
- Problem solving and critical thinking.

ESCO provides two key rules to help identify digital skills:
1. Skills that explicitly mention the exclusive use of digital tools to achieve their goal. For example, skills such as "coordinate advertising campaigns" and "monitor traffic flow" are excluded from digital skills, as they do not necessarily require the use of digital tools.
2. Skills that capture activities where the main goal or core of the activity lies in the digital domain. Skills such as "troubleshoot website" and "maintain computer hardware" are included in digital skills, as their primary focus is on the use of digital technologies.

Based on these definitions, our working definition of digital skills is: "All skills that involve the use of a computer", where a computer can also be a smartphone or tablet. According to this definition, both "composing business emails" and "Java (computer programming)" fall under digital skills. Skills such as writing an email or using a laptop to diagnose a car's malfunction are also considered digital skills.

However, there are some grey areas in the classification of digital skills. For example, electro-technique skills and mechanical skills in a digitalized industry may be difficult to categorize. Skills such as "assemble hardware components", "assemble telecommunications devices", and "assemble robots" are included in the list of digital skills, as they involve the use of digital tools and technologies. In contrast, skills such as "install car electronics" and "build bodies for vehicles" are not classified as digital skills, as they do not necessarily require digital literacy.

Although skill ontologies do have several limitations, it is important to recognize that skill ontology-based indicators offer distinct advantages over those derived from survey data. Survey-based indicators often suffer from a lack of detail regarding the variety of tasks and skills, as well as from biases stemming from respondents' self-reported perceptions. In contrast, ontology-based indicators provide a more structured and consistent representation of skill requirements, reflecting the substantial effort invested by experts in developing these ontologies (Lennon, Zilian, and Zilian, 2022).

We followed these concepts when we defined digital skills within the CompetentNL ontology. The subsequent sections provide a more detailed explanation of skill ontologies and how digital skills are identified within this CompetentNL ontology.

3. Skill ontologies

We investigate digital skills within two skill ontologies, ESCO and CompetentNL. These frameworks provide structured classifications of skills, professions, and competencies, enabling better alignment between education, training, and labor market needs. Both of these ontologies ESCO and CompetentNL are being updated to be up to date concerning occupations and skills. The updates are based on new skills and tasks collected from the vacancies on European and national levels.

3.1 European skills qualifications competencies and occupations (ESCO)

ESCO is an ontology developed by the European Union to standardize the description of skills, qualifications, and occupations across member states. It includes over 3,000 professions and 14,000 skills, available in 28 official EU languages. The results are not affected by the choice of language. Digital skills in ESCO are identified through a five-step methodology that combines human labeling based on the DigComp 2.2 framework and machine learning algorithms using vacancy texts[6]

[6] Mapping DigComp digital competences to the ESCO skills framework for analysis of digital skills in EU online job advertisements | European Skills, Competences, Qualifications and Occupations (ESCO)

ESCO skills are structured in a hierarchy that contains four sub-classifications: knowledge (K), language skills and knowledge (L), skills (S) and transversal skills (T). ESCO skills include both 'skill/competence' and 'knowledge. There are around 124 thousand connections between about 3000 different ESCO occupations and 14 thousand different skills. All data can be downloaded from the ESCO website[7].

Besides the skills that are allocated to occupations, ESCO defines Transversal skills and competences that are not assigned to specific occupations. Transversal skills are abilities which are commonly seen as necessary or valuable for effective action in practically for any kind of work, learning or life activity, these are for e.g. foundations for interacting with others and for developing and learning as an individual. They comprise the ability to understand, speak, read and write language(s), to work with numbers and measures and to use digital devices and applications. Some of the transversal skills are obvious digital skills, e.g. ‘apply basic programming skills’, ‘use spreadsheets software’. If a profession contains digital skills that are all transversal, this profession will not score as digital, while it is a digital profession according to the definition above. Identifying digital professions could have been done using transversal skills if these were linked to professions.

Skills in ESCO has 5 sub-levels. Table 1 gives an example of the skills hierarchy within category S5 "working with computers".

Table 1: Skill Hierarchy in ESCO

S5 - working with computers	−
S5.0 - working with computers	−
S5.0.0 - working with computers	−
- analyse ICT system	−
- identify ICT system weaknesses	
- assemble hardware components	
- maintain ICT server	−
- manage ICT virtualisation environments	
- maintain ICT system	+

When linking skills with the occupations other concepts are also defined: the reusability level and whether the skill is essential or optional for the occupation. The reusability level of a skill is defined by looking at whether it is transversal, cross sectoral, sector specific or occupation specific. For each skill there are associated occupations for which this skill is essential and occupations for which this it is optional. For each occupation for each linked skill, it is defined whether a skill is essential or optional.
There are 5 occupation levels defined within ESCO. Table 2 gives an example of two occupation groups from the highest to the lowest levels: from 2-Professionals

[7] The skill-occupation links are not in the zipfile with Dutch-language files that are downloaded. These can only be found in the 'language independent' download.

Table 2: Occupation levels in ESCO

up to 2120.6.1-biometrician and from 9-Elementary occupations to 9123.1-window cleaner. Note that for the second case there are only four levels.

2 - Professionals	–
21 - Science and engineering professionals	–
211 - Physical and earth science professionals	+
212 - Mathematicians, actuaries and statisticians	–
2120 - Mathematicians, actuaries and statisticians	–
2120.1 - actuarial consultant	
2120.2 - demographer	
2120.3 - gambling games developer	
2120.4 - gambling quality assurance engineer	
2120.5 - mathematician	
2120.6 - statistician	–
2120.6.1 - biometrician	

9 - Elementary occupations	–
91 - Cleaners and helpers	–
911 - Domestic, hotel and office cleaners and helpers	+
912 - Vehicle, window, laundry and other hand cleaning workers	–
9121 - Hand launderers and pressers	+
9122 - Vehicle cleaners	+
9123 - Window cleaners	–
9123.1 - window cleaner	

3.2 CompetentNL and CNL-UWV

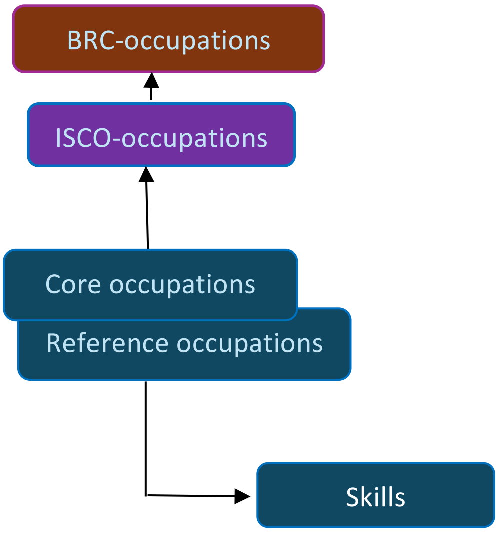
CompetentNL is a broad national collaboration of government institutions: The Employee Insurance Agency (UWV)[8], Vocational Education, Training and the Labor Market (SBB)[9], TNO (The Netherlands Organization for Applied Scientific Research)[10] and Statistics Netherlands. This collaboration aims to create a national standard for describing skills, a so called 'skills language', to understand which skills are needed in vacancies, profiles, training and courses and to further improve the connections between the labor market, education and people.

For this research, we used one of the products of CompetentNL: a draft version of the CNL-UWV dataset. The CNL-UWV links occupations from the UWV occupational register to CompetentNL skills. It is a drat version as both the content and structure of the CNL-UWV tables are still under development. We refer to the dataset simply as CNL-UWV throughout the remainder of this paper. The dataset is available in Dutch language only. Labels in English in this paper were translated by the authors.

[8] https://www.uwv.nl/
[9] Vocational education Labour Market
[10] https://www.tno.nl/

Data we use for our research are links between the 'core occupations’ and the 'skills', see Figure 1. These occupations are also linked with the ISCO and BRC occupations. The skills in CNL-UWV contain a broad match with ESCO skills. CNL-UWV provides 19,913 links between skills and 774 core occupations. Many of the same skills are linked to different occupations. In Appendix C Table C1 the skills are given that are linked to the occupation 'ICT system developers and analysts'.

Figure 1: Skills and occupations in CNL-UWV



The corresponding occupation in ISCO is 'System analysts and ICT advisors' and in BRC 'Software and application developers' in BRC.
The 'reference' occupations are more detailed than the 'Core occupations', these are not yet linked with skills.

For CNL-UWV data we identified digital skills. In Section 4 we describe how we define digital skills and Section 5 we present obtained results.

3.3 CNL-UWV vs ESCO

Key differences between the two frameworks are summarized in Table 3. The table shows the details of the number of professions and skills in CNL-UWV and ESCO. ESCO contains almost four times as many professions and almost three times as many skills are distinguished.

Table 3: Skills and occupations in ESCO and CNL-UWV

	CNL-UWV	ESCO
Occupations	774	3,006
Optional and essential skills	4,617	13,117
Essential skills	2,626	10,945

Distribution of skills per occupation is quite uneven in both ontologies. At CNL-UWV, 'Sales employees retail non-food (other)' have the most skills (85). If we look at only essential skills, 'Forest and nature management employees' and

'Electricians and installers of electrical installations' have the leading position with 36 essential skills. 'Meter readers and traffic counters' and have only 1 essential skill ('preparing policy and advice reports').

At ESCO, 'sales specialists' are at the top by the number of skills (340). Among the essential skills, 'chiropractors' are considered the profession with the most skills (133). For an 'energy advisor' or 'linen room employee', only two skills are essential.

3.4 Classification ESCO and CNL-UWV occupations

Both ESCO and CNL-UWV ontologies use international classification systems for mapping occupations with skills. ESCO and CNL-UWV both are aligned with ISCO. For publications in the Dutch national context within SN uses the BRC2014 classification of occupations. The ISCO occupations are linked with BRC2014.

ISCO occupational classification:
The ISCO is an ILO (International Labor Organization) classification structure for organizing information on the labor market and employment. This is a hierarchical classification with 4 levels. The least detailed level distinguishes 10 major groups of occupations. The most detailed level, “unit groups”, has 436 different occupations.

BRC 2014 Occupation Classification:
BRC2014 and ISCO share the same format but BRC2014 is somewhat different from ISCO, as some of ISCO groups are less relevant for the Dutch economy. BRC2014 has 114 occupation levels. Multiple ISCO codes can fall under one BRC2014 code.

Table 4 gives the ESCO and CNL-UWV occupation distribution according to BRC2014 on highest level. We should mention that 11 out of 773 occupations in CNL-UWV could not be linked to any BRC2014 occupations.

Table 4: ESCO and CNL-UWV occupations grouped according to BRC 2014

		Occupations			
BRC2014		**ESCO**	**CNL-UWV**	**ESCO**	**CNL-UWV**
01	Pedagogical professions	169	39	6%	5%
02	Creative and linguistic professions	175	38	6%	5%
03	Commercial professions	179	52	6%	7%
04	Business economics and administrative professions	298	89	10%	12%
05	Managers	325	64	11%	8%
06	Public administration, security and legal professions	105	46	3%	6%
07	Technical professions	1181	210	39%	28%
08	ICT professions	91	21	3%	3%
09	Agricultural professions	57	23	2%	3%

10	Care and welfare professions	208	90	7%	12%
11	Service professions	110	49	4%	6%
12	Transport and logistics professions	108	41	3%	5%
Total		3006	762	100%	100%

Observe that in ESCO a relatively large number of technical occupations as distinguished, while CNL-UWV has a relatively large number of healthcare occupations. Other groups are relatively similar.

4. Digital skills and digital scores

In this section we define digital score for occupations based on digital skills. As mentioned above, ESCO already has a list of digital skills defined for occupations on ISCO-4 level. For CNL-UWV, we did not have such a list. Below we explain how we identified digital skills within CNL-UWV.

The following sub-sections describe an algorithm to identify digital skills within CNL-UWV, also how we identified digital terms and how we defined complexity of digital skills (Section 4.1), the construction of digital score for occupations in ESCO and CNL-UWV (Section 4.2), and the aggregated digital scores for occupations for ISCO and BRC classifications (Section 4.3).

4.1 CNL-UWV digital skills

As we discussed above to identify digital skills within CNL-UWV we follow the definition used by ESCO. In short this means to identify "all skills involving the use of a computer" as digital skills. Here 'computer' should be interpreted in a broader sense, including also smart devices such as smartphones or tablets and other digital data machines. According to this definition skills such as e.g. "composing business emails" and "Java programming" fall under digital skills, but also the skills such as “entering data in a database” is a digital skill.

We carried out the following steps recursively and stopped when the complete list of skills had been exhausted:

1. **Search for the occupations that include digital term(s):** We used 'ICT' as the starting point. In the first round we look for all occupations that include ‘ICT’, these are for e.g. "ICT professionals in geo-information systems", "ICT systems designers and analysts".
2. **Identify skills**: Find skills linked to the occupations found in step 1. This step results into a list of all skills of all occupations from step 1.
3. **Find new digital terms**: Look at the skills descriptions from step 2 to identify digital terms. This is done manually, for example by searching for words that

describe digital skills, such as 'data', 'technical', 'analyze', 'IT applications' and 'information technology infrastructure'. The result is a list of digital terms.
4. **Identify skills with digital terms:** Search for skills that contain the digital terms from step 3. The result is a list of digital skills.
5. **Identify digital occupations:** Search for new occupations that are linked to the skills from step 4 and that are not already in the list from step 1
6. **Identify new skills:** Search for all skills that are linked to the occupations found in step 5. This step produces a list of all skills of the occupations from step 5. The skills that were already found in step 2 are removed from this list.
7. **Find new digital terms:** Manually search for digital terms in the list of skills from step 6. Remove digital terms that were already found in step 3.
8. **Repeat:** Repeat steps 4 till 7 until there are no new digital terms to be found.

For CNL-UWV data, steps 3 and 7 were carried out manually without applying machine learning (ML) techniques as the list of 4.6 thousand skills was manageable. For a larger list one could use ML models to search for digital terms. In (Lennon, Zilian en Zilian 2022) authors identified digital skills based on a similar iterative algorithm within ESCO, using ML model.

4.1.1 Relevance of digital terms in identifying digital skills

During our search for digital terms, we experimented with including terms like “install,” “technical,” "systems" and “analyze” to detect digital skills. However, we observed that such terms also appear in many non-digital skills. For example, “Install” appears in manual or construction-related skills, “Technical” is widely used in non-digital contexts, and “analyse” occurs frequently in strategic, business, or social skills:

“Install”
- Install fire extinguishers
- Install floor heating

“Technical”
- Provide technical support
- Develop technical and financial solutions
- Develop technical files
- Check technical feasibility of products

“Analyse”
- Analyse the potential of a business customer market
- Analyse a situation, context or service provision
- Analyse job profiles in companies

"Systems"
- Adjusting and checking mechanical systems, installations, and tools
- Checking the quality of mechanical systems
- Maintaining and repairing specific truck systems
- Maintaining air conditioning systems

We decided that these terms alone are not reliable indicators of digital skills and require contextual validation or co-occurrence with more specific digital terms. Therefore, we did not include these in our list of digital terms.

4.1.2 Non-digital terms for digital skills

We have observed that in CNL-UWV, there are quite a few skills that initially appear to be non-digital. However, upon closer examination, we are almost certain that these skills are, in fact, digital as they are typically carried out using digital devices. A vivid example is the skill "administrate files." Several decades ago, this skill could have been performed using pen and paper without the need for a computer. However, in today's digital age, it is highly unlikely that this task is carried out without the use of digital tools such as file management systems, cloud storage, or office software. This shift underscores the evolving nature of skills and the increasing reliance on digital technologies across various domains.

Another illustrative example is a skill that includes the term "analyse results." It is difficult to imagine that, in the current context, results are being analysed without the use of digital tools. Whether through statistical software, data visualization platforms, or even basic spreadsheet applications, digital devices are now indispensable for performing such tasks efficiently and effectively. There are quite a few such terms and skills in the CNL-UWV framework that, while not explicitly marked as digital, are in practice carried out using digital means. In Appendix A, we provide a list of these terms.

By identifying and including these non-digital terms, our goal was to find additional digital skills that may have been previously overlooked or underestimated. We found in total 47 additional skills, these were: "Registering material use and labor hours", "Preparing analysis reports", "Maintaining pharmacy registers and documentation", "Administering customer payments", "Preparing architectural drawings", "Data typing", "Preparing documents", "Writing research reports and articles", ect. These 47 skills identified 234 occupations as digital, however most of these occupations were already identified as digital as they were also linked with other digital skills. From these 234 occupations only extra 24 occupations were not yet identified as digital. Here is a list of some of these occupations: "Tax specialists", "Civil engineering consultants", "Soil researchers and road construction material analysts", "Civil engineering project managers", "Electrical engineering project managers", "Construction inspectors and consultants", "Pharmacy assistants", "Police inspectors and detectives", etc. Hence the gain from this extra step was little.

In Section 5, we present the results of our analysis including these additional digital skills.

4.2 Complexity of digital skills in CNL-UWV and ESCO

Skills identified as digital within the CNL-UWV data vary significantly in complexity. The same holds for digital skills in the ESCO ontology. For instance, there is a notable disparity in complexity between digital skills like "work with Microsoft Word" or "develop a software tool". This and other issues created the need to rank digital skills by complexity for refine digital scores for occupations.

The concept of skills complexity is not a new topic and is widely discussed in the literature, often in relation to the job market and productivity[11], but also in contexts linking education to required skills[12] or supporting individuals with skill assessment for education and job-seeking[13]. In the literature both objective and subjective dimensions are investigated while measuring and ranking skill complexity. Objective complexity relates to the inherent characteristics of a skill, while subjective complexity depends on the person performing the task. As tasks are directly linked with skills, tasks of high complexity require better skills than tasks of low complexity. However subjectively the same task can be complex for one person and simple for the other. To assess subjective skill complexity ranking scale was developed by e.g. (Maynard en Hakel 1997) or (Steele-Johnson 2000), (Nadolski, et al. 2005). There are various approaches for measuring skill complexity based on proficiency levels[14]. Proficiency levels help quantify how skilled a person is in a specific task.

Similarly to (Nadolski, et al. 2005) we look at the complexity of digital skills. In our study four authors of this paper independently rated each digital skill within CNL-UWV and ESCO ontologies. We applied 3-point ranking scale: high, medium, or low rank for **digital competence** of each skill. Main guidelines for this ranking were:

- **Low**: These skills require basic digital knowledge, using digital devices to obtain information and assess it for the correct value, work with email, write a digital report. In our society this is gradually becoming a requirement for everyone.
- **Medium**: This level is more complex and requires the knowledge of specialist software (e.g. CAD or GIS) and data analysis to practice a profession.
- **High**: Skills for software developer, ICT – expert who can manage hardware and software, networks, information systems, etc. at a technical level.

Table 5 illustrates the level of agreement among the researchers when assigning complexity scores for digital skills. Full agreement among all 4 researchers was rare for both CNL-UWV and ESCO skills, it occurred in only around 28% of cases. In all cases (100%), at least two researchers agreed, which is expected to happen when you have only three levels and four raters. The level of partial agreement is high, but full consensus is limited, suggesting some subjectivity in interpreting skill complexity, even with a shared conceptual framework.

Table 5: Agreement between assigned scores

	All agreed	3 agreed	2 agreed
CNL-UWV	28.6%	67.3%	100%
ESCO	27.7%	70.6%	100%

We calculated the concordance coefficient Light’s kappa (Conger 1980) that is extension of Cohen’s Kappa for are more than 2 raters. It showed that the

[11] Skills, Tasks, and Complexity
[12] SkillPlan_Digital-Skills-EN.pdf
[13] Education+and+Skills+Online.pdf
[14] What are Proficiency Levels? A Guide to Skill Assessment | TalentGuard

concordance between the raters is fare. In Appendix B we elaborate more on these findings.
For each digital skills we have 4 complexity weights $w_{jk},\ k = 1, \ldots, 4$. To combine these complexity weights, we use the function 'mode'. The mode for a categorical variable is the value that appears the most often in the realization of the variable. When there are two modes, we use the largest value[15]. In Appendix C for the occupations 'ICT system developers and analysts' and 'Accountants' of CNL-UWV we present the tables of all skills linked to these occupations and the mode of the complexity weights of the digital skills.

4.3 Digital scores for occupations

We developed three different approaches to define a digital score for occupations:
- **Weighted sum** method calculates digital score as a weighted sum of all digital skills (both essential and optional).
- **Mode of complexity rank** method uses the ranking of skills by their level of complexity and the mode function.
- **Highest rank** approach also uses the complexity ranking and mode function, but it focuses on the most complex digital skill required by the occupation.

In the first two methods, we apply a penalty λ to optional skills, meaning that the weight for the optional skills is less than 1 ($\lambda < 1$), while essential skills have a weight equal to 1. Because λ is somewhat subjective, we tested whether varying λ affected the digital scores substantially, which was not the case. Also including or completely omitting optional skills leads to minimal differences on aggregated levels, see Appendix D.

We will elaborate below on the limitations of all three approaches. Should note that the second and third approaches were designed to address data limitations that the first method could not handle. In Appendix C we derive digital scores for three different occupations following these three approaches.

Weighted sum. This method resembles the approach used by (Lennon, Zilian en Zilian 2022), where a Digital Competence Indicator (DCI) is calculated for each occupation. The DCI is defined as the ratio of digital skills in a specific occupation compared to the share of digital skills across all occupations.

We applied the weighted sum method to both ESCO and CNL-UWV data. For each occupation, the digital score is defined as the weighted sum of all required digital skills. For each skill j we define the digital weight w_j, where we assume that:
- $w_j = 1$ for digital skill,
- $w_j = 0$ for non-digital skill.

[15] These results did not include the 'additional digital skills' identified in Section 4.1.2. These skills were treated differently from the others, as they were originally based on non-digital terms. However, based on our analysis, we are certain that a minimal level of digital literacy is required to perform these tasks. As a result, we rated these skills as "low" in terms of digital proficiency.

We applied a penalty ($\lambda < 1$) to optional skills. This way we try to reduce the impact of optional skills on the digital score.
The weighted sum digital score for an occupation is defined as:

$$\text{Digital Score} = \frac{1}{n^{ess}} \sum_{j}^{n^{ess}} w_j + \lambda \frac{1}{n^{opt}} \sum_{j}^{n^{opt}} w_j, \qquad (1)$$

here n^{ess} and n^{opt} denote the number of essential and optional skills for an occupation. We have

$$n^{skills} = n^{ess} + n^{opt}.$$

n^{skills} is the number of skills linked with an occupation.

Note that the highest possible digital score that can be obtained using this method is equal to $1 + \lambda$ and it can be obtained if an occupation has only digital skills (with at least one optional digital skill). Observe that in this case it does not matter how many skills this occupation has. Also, if an occupation has only digital essential skills it will get a score equal to 1.

To explain better this method, let us assume that we have an occupation with 5 skills that are all digital, say 3 are essential and 2 are optional. Then the weighted sum digital score for this occupation is $\frac{1}{3}\sum_j^3 1 + \lambda \frac{1}{2}\sum_j^2 1 = 1 + \lambda$. Now consider another occupation, having 10 essential digital and 5 optional digital skills and 10 non-digital essential skills and 5 non-digital optional skills. For this occupation the weighted sum digital score is $\frac{1}{20}\sum_j^{10} 1 + \lambda \frac{1}{10}\sum_j^5 1 = \frac{1}{2} + \frac{\lambda}{2} = \frac{1}{2} * (1 + \lambda)$, that is half of the score of the first occupation.

The weighted sum method provides a digital score that reflects how digital an occupation is relative to all skills it has. To use this method, one needs a uniform skill ontology, meaning that the distribution of the number of skills for occupations should preferably have close to uniform distribution. If we have many occupations with 2-5 skills or 50 - 60 skills, the weighted sum method will not be able to give a reasonable score.

In the following analyses, λ is always set to 0.5.
Example:
Suppose we have an occupation with 25 skills, 10 of which are essential and 15 are optional. Of these 10 essential skills 3 are digital and of 15 optional skills 4 are digital. The digital score is calculated as:

$$\text{Weighted sum score} = \frac{1}{10} \sum_{j}^{10} w_j + 0.5 \frac{1}{15} \sum_{j}^{15} w_j = \frac{3}{10} + 0.5 \frac{4}{15} = 0.43 \qquad (2)$$

Here $\lambda = 0.5$.

Mode of complexity rank. As described in section 4.2, we classified digital skills from CNL-UWV and ESCO according to their level of complexity: high, medium and low in terms of digital competence. For digital skills we have:

$$w_j = \begin{cases} 1 \; low \\ 2 \; medium \\ 3 \; high \end{cases}$$

As above $w_j = 0$ for non-digital skills. Each project member assigned the level of complexity to each digital skill. We have 4 values for $w_{jk},\ k = 1, \dots, 4$ for each skill. To combine these complexity weights, we use the function 'mode'. The mode for a categorical variable is the value that appears the most often in the realization of the variable. When there are two modes, we use the largest value.
The digital score is defined as follows:

$$\text{Mode of complexity score} = \frac{1}{n^{ess}} \sum_{j}^{n^{ess}} \text{mode}_k(w_{jk}) + \lambda \frac{1}{n^{opt}} \sum_{j}^{n^{opt}} \text{mode}_k(w_{jk}).$$

As above, we apply a penalty for optional skills. Note that the highest possible digital score that can be obtained using this method is $3(1 + \lambda)$. This will occur when all digital essential and all digital optional skills have high complexity mode equal to 3 and there are 0 non-digital skills. As with the previous method, the digital score reflects how digital an occupation is relative to all the skills it has. However, this method adds the nuance of the complexity of digital skills—more complex digital skills result in a higher score.

Example:
Suppose we have an occupation with 25 skills, 10 of which are essential and 15 are optional. Of these 10 essential skills 3 are digital and of 15 optional skills 4 are digital. Suppose the 3 digital essential skills had been ranked so that the mode is (2,1,1) and for 4 digital optional skills the mode is (1,2,1,1). The mode of complexity score when $\lambda = 0.5$ is:

$$\begin{aligned} &\text{Mode of complexity score} \qquad (2) \\ &= \frac{1}{10} \sum_{\text{j}}^{10} \text{mode}_k(w_{jk}) + 0.5 * \frac{1}{15} \sum_{\text{j}}^{15} \text{mode}_k(w_{jk}) \\ &= \frac{2+1+1}{10} + 0.5 * \frac{1+2+1+1}{15} = 0.567. \end{aligned}$$

If we calculate the weighted sum score, in (3) for this example we observe that the scores are not very different. This is due to relatively low complexity scores in this example.
The weighted sum digital score is:

$$\begin{aligned} \text{Weighted sum score} &= \frac{1}{10} \sum_{j}^{10} w_j + 0.5 \frac{1}{15} \sum_{j}^{15} w_j = \frac{3}{10} + 0.5 \frac{4}{15} \qquad (3) \\ &= 0.43 \end{aligned}$$

Highest rank. When not all digital skills that are required are listed the score defined by the first two approaches not be uniformly defined for different occupations. To make a method that is less dependent on not having all digital skills required for an occupation base the digital score on the most complex essential digital skill. The assumption is that the most complex digital skill required will be explicitly mentioned in the ontology. While less complex digital skills may be omitted in the data.

Here again, the mode for each skill has been calculated based on the assessment of the four researchers, whereby the highest rated essential digital skill for each CNL-UWV or ESCO occupation is considered for the digital score:

$$\text{Highest rank score} = \max_{j \in ess}\{\text{mode}_k(w_{jk})\}.$$

Example:
As we assumed above in our example the 3 digital essential skills had been ranked so that the mode was (2,1,1). With the highest rank the digital score will be

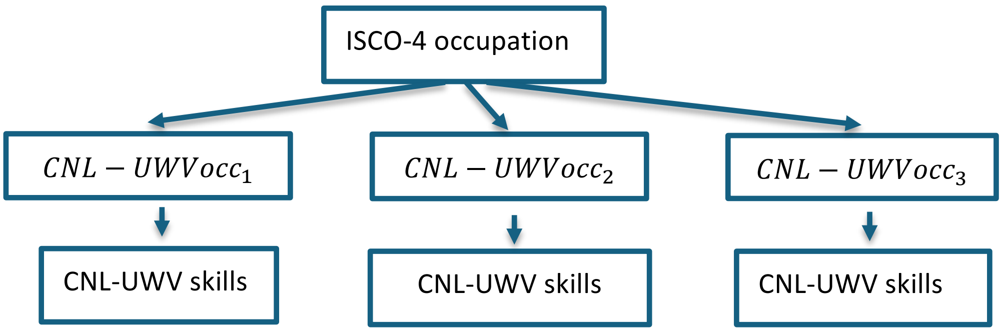
$$\text{Digital Score} = \max_{j \in ess}\{\text{mode}_k(w_{jk})\} = \max_{j \in ess}\{2,1,1\} = 2.$$

4.4 Digital scores for ISCO and BRC classifications

Both CNL-UWV or ESCO data are linked with ISCO occupations on 4 digit level (ISCO-4). To define the digital score for an occupation on ISCO-4 level we consider all occupations from CNL-UWV or ESCO and all underlying skills.

To illustrate this, suppose that an ISCO-4 occupation is linked with three CNL-UWV occupations, see Figure 2. All skills from these three occupations are now considered to be the skills of ISCO-4 occupation. Now derive the digital score for ISCO-4 occupation following the approaches defined in the previous section. Note that some of the skills could be included more than once. It will occur if the $CNL - UWVocc_1$, $CNL - UWVocc_2$ or $CNL - UWVocc_3$ occupations have some of the same skills. Similarly, we define the digital score for ISCO-4 occupations based on ESCO data.

Figure 2: Linking ISCO-4 occupation with CNL-UWV skills



In order to define the digital score for a higher level for BRC 2 (12 professional groups), all combinations of the underlying detailed occupations have been included within an ISCO unit group. A weighted average has been calculated based on the share of digital skills of each ISCO unit group within a BRC occupation group, using *the number of employees* in 2023 per ISCO unit group as a weighting factor.

5. Results

In the previous section, we described the approaches we used to define the digital score. This section presents the intermediate and final results. The results for CNL-UWV are based on the digital skills identified in Section 4.1.

5.1 Digital skills and digital occupations in ESCO and CNL-UWV

Following the scheme outlined in Section 4.1, we identified digital skills within the CNL-UWV data. In Table 6, we compare the totals of digital and non-digital skills in both CNL-UWV and ESCO. Note that in ESCO, digital skills make up approximately 8.96% of all skills (1,175 out of 13,117), whereas in CNL-UWV, they account for around 7.3% (338 out of 4,617). These figures are broadly compatible.

Table 6: ESCO vs CNL-UWV skills

	Digital	Non-digital	Total
CNL-UWV			
Number of essential skills	235 (8.95%)	2 391 (91.05%)	2 626
Total number of skills	338 (7.32%)	4 279 (92.68%)	4 617
ESCO			
Number of essential skills	924 (8.44%)	10 021 (91.56%)	10 945
Total number of skills	1 175 (8.96%)	11 942 (91.04%)	13 117

However, when comparing the percentage of digital occupations (occupations that are linked to at least one essential or optional digital skills) in CNL-UWV and ESCO, we observe that CNL-UWV contains a relatively higher share of digital occupations: 75.4% compared to 67.3% in ESCO. Similar results are found when examining the links between skills and occupations. In CNL-UWV, 9.9% of all skill-occupation links are digital, compared to 7.1% in ESCO, see Table 7. This could be because CNL-UWV lacks professions that do not fit the Dutch economy.

Table 7: ESCO vs CNL-UWV occupations

	Digital	Non-digital	Total
CNL-UWV			
Occupations	583 (75.4%)	190 (24.6%)	773
Links between skills and occupations	1 977 (9.9%)	17 936 (90.1%)	19 913
ESCO			
Occupations	2 021 (67.3%)	983 (22.7%)	3 004
Links between skills and occupations	8 817 (7.1%)	115 038 (92.9%)	123 855

In the ESCO ontology, the most common skill is 'create solutions for problems', which is required by 350 different occupations. Among digital skills, 'having computer skills' is the most common, occurring in 238 occupations. In CNL-UWV, the most common overall skill is 'coordinating team activities', which is required by 252 occupations. Among digital skills in CNL-UWV, 'performing administrative tasks' is the most common, occurring in 155 occupations. In Table 8 and Table 9, we list the top 6 most common overall and digital skills, along with the number of occupations in which they occur in both ESCO and CNL-UWV.

Table 8: Most common skills.

Skills	Frequency
ESCO	
Create solutions for problems	350
Use different communication channels	341
Lead staff	330
Keep track of work progress data	323
Have computer skills	317
Quality standards	315
CNL-UWV	
Coordinating team activities	252
Managing stock	190
Performing administrative tasks	155
Leading departments or organizations	142
Managing budgets	132
Assessing stock requirements	121

Table 9: Most common digital skills.

Digital Skills	Frequency
ESCO	
Have computer skills	317
Install machine operation	157
Monitor automatic machines	156
Electronics	143
Technical drawings	141
Use CAD software	138
CNL-UWV	
Performing administrative tasks	155
Filling in work documents and reporting data	76
Processing information	68
Performing accounting management	62
Analyzing activity data	51
Analyzing research data	50

Observe that there is a significant difference in the frequency of skills between ESCO and CNL-UWV. However, considering that CNL-UWV is a relatively small ontology, these frequencies are reasonable.

If we look at the occupations within ESCO, 'application engineer' is linked to 111 digital skills, making it the occupation with the highest number of digital skills. It is followed by 'database developer', which is linked to 104 digital skills. In CNL-UWV, 'network specialists' have the highest number of digital skills (21), followed by 'ICT Security specialists ' with 19 digital skills. Table 10 gives the top 6 occupations with most digital skills.

Table 10: Occupations with highest number of digital skills

Digital Skills	Frequency
ESCO	
Application engineer	111
Database developer	104
Electrical engineer	102
Data warehouse designer	100
Database designer	94
User interface developer	92
CNL-UWV	
Network specialists	21
ICT Security specialists	19
Application programmers	17
Techno-hardware managers	17
Telecommunications designers	16
Website management specialists	16

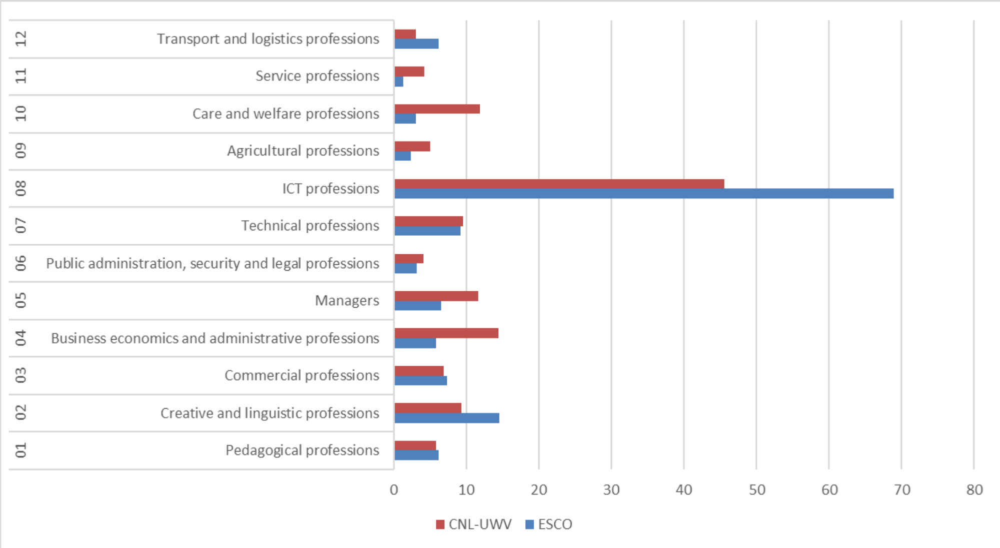
It is important to note that the number of skills per occupation is not uniform across both datasets. Some occupations are associated with a large number of skills, while others have very few. Additionally, certain digital skills that are considered obvious for an occupation are not included. For example, 'lawyers' are not linked to a skill such as 'manage the email', as it is assumed that they naturally possess this ability.

5.2 Aggregated digital scores

If we look at the aggregated digital scores values, we observe in both tables that ICT professions are clearly represented but only make up a subset of all digital skill-relevant roles. From the tables above we observed that ESCO has a higher digital skill density than CNL-UWV. That is not surprising as CNL-UWV data we used, is a draft version is still being developed. However, from the Figures 4, 5 and 6 we see that for the aggregated digital score on BRC 2-digit level for ESCO and CNL-UWV the difference is not that big. Figures show the digital scores based on three methods defined above. To make results for ESCO and CNL-UWV data comparable the final scores are multiplied by $\frac{100}{1+\lambda}$ and $\frac{100}{3(1+\lambda)}$ respectively for the weighted sum and the mode of complexity rank methods. By multiplying the scores with these factors, we ensure that its range is [0, 100] for both ESCO and CNL-UWV.
For the results in Figures 3, 4 and 5 $\lambda = 0.5$. We compared the results of the digital score derived for BRC aggregates for different values of λ. We observed a gradual,

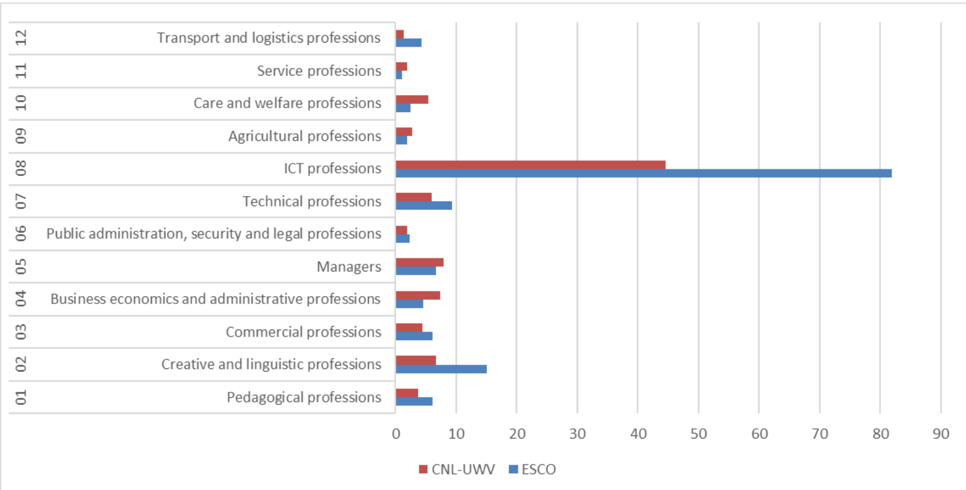
but minor change in the score when varying λ from 0 to 1, see Appendix D. For this reason, we set λ to be 0.5.

Figure 3: Digital occupations on BRC 2-digit level, weighted sum method



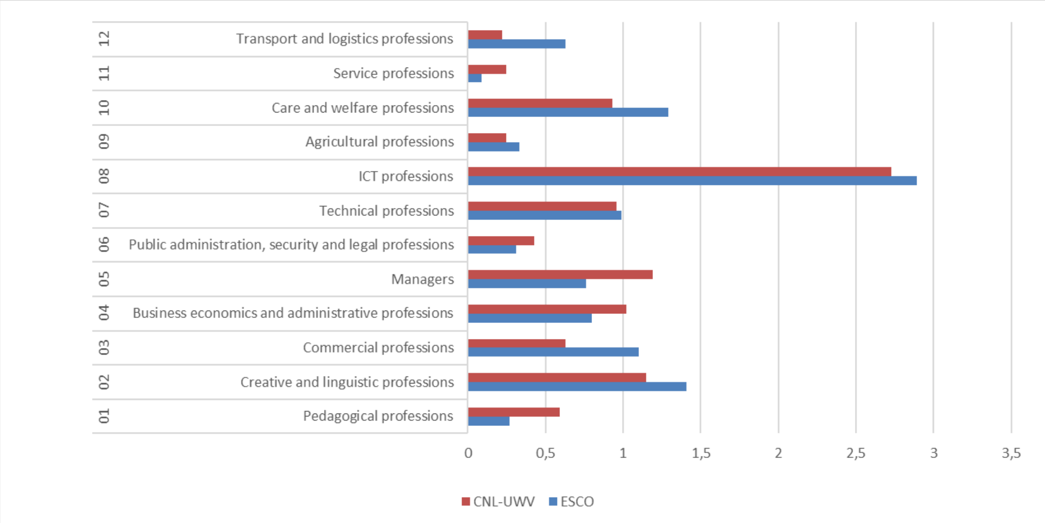
Including complexity level of the skills, in the mode of complexity rank method did not change the overall digital scores on BRC 2-digit level, see Figure 4. Here as well we observe large difference for ICT professions between ESCO and CNL-UWV data. For other professions we observe that for some ESCO has higher digital score and for others CNL-UWV.

Figure 4: Digital occupations on BRC 2-digit level, mode of complexity rank



As mentioned above, we applied the highest rank method to address several issues in our data. Figure 5 shows the results obtained using this approach. We observe that the digital scores are more similar between our two data sets. However, this is, in a way, a blunt approach that focuses only on the most complex essential digital skill.

Figure 5: Digital score per occupation based on the most advanced essential digital skill (BRC 2-digit)



From the presented figures, it is evident that at the aggregate level, the weighted sum method yields the greatest discrepancies between ESCO and CNL-UWV data. In contrast, the digital score based on the most advanced essential digital skill, as illustrated in Figure 5, demonstrates the smallest differences between the two datasets. Should the comparability of ESCO and CNL-UWV data be considered a key criterion for evaluating the digital score method, the third method would be preferred. A more detailed discussion of the relative merits and preferences among the various methods will be provided in the final section of this paper.

5.3 Comparison of digital score and ISCO - level for ESCO and CNL-UWV data

In Table 11 we compare the ISCO 1 till 4 occupation levels and the digital level of ESCO and CNL-UWV groups determined according to the method of Highest rank. We observe that in ESCO and CNL-UWV, 40% and 36% of the occupations at the highest ISCO level respectively receive a digital score of 0, which means that none of the skills of these occupations are classified as digital. This group includes, for example, directors, managers and mayors. As mentioned above given the occupational level, certain digital skills are considered self-evident in both ESCO and CNL-UWV data which means that a number of occupations, such as high education teachers or lawyers, are wrongly classified as occupations without digital skills. These occupations do not have an inherently digital character, but it is very unlikely that no digital skills are required for these occupations.
Another interesting result here is significant difference in the complexity level 1 between ESCO and CNL-UWV data. In CNL-UWV we have relatively more occupations that are assigned low complexity level (33% vs 19%) and much less occupations having high complexity level (3% vs 11%).

Table 11: Digital occupations within ISCO

	ISCO level

Digital score occupation ESCO	1	2	3	4	Totaal
0	85%	61%	54%	40%	52%
1	9%	19%	19%	20%	19%
2	5%	15%	16%	20%	17%
3	0%	4%	10%	20%	11%
	ISCO level				
Digital score occupation CNL-UWV	1	2	3	4	Totaal
0	77%	54%	43%	34%	46%
1	23%	35%	38%	29%	33%
2	0%	10%	17%	29%	18%
3	0%	1%	2%	8%	3%
* ISCO level					
1: Simple routine tasks; elementary or lower education required.					
2: Tasks of low to moderate complexity; primary or secondary education required.					
3: Complex tasks; secondary or higher education required.					
4: Highly complex specialized tasks; higher or academic education required.					

6. Discussion

This paper presents an analysis of digital skills and occupations, based on two skill ontologies: ESCO and a draft version of CNL-UWV, and explores methodological approaches to defining occupation-level digital scores. Both data frameworks establish linkages between (digital) skills and occupations, yet they differ significantly in the depth of these mappings. ESCO offers a broad, multilingual, and internationally recognized framework, making it particularly well-suited for cross-national comparative analyses. In contrast, CNL-UWV provides a more granular and nationally focused representation, tailored specifically to the Dutch labor market.

Unlike ESCO, CNL-UWV does not include predefined digital skills or digital occupations. Therefore, the first step in our analysis involved identifying relevant digital skills and occupations within the CNL-UWV dataset. Based on this identification, we developed three approaches to calculate a digital score for occupations, drawing on data from both ESCO and CNL-UWV:

- The first approach did not account for the complexity of skills, a critical factor in distinguishing between basic and advanced digital competencies.

To address this limitation, we introduced a three-level ranking of skill complexity, which was subsequently integrated into the second and third methods.

- The third method was specifically designed to overcome the shortcomings associated with the absence of implicit digital skills—particularly in occupations requiring middle or higher education levels, where such skills are often assumed but not explicitly stated. While this approach only partially resolved the issue, as some occupations lacked any explicit digital skill references, it marked an important step toward a more comprehensive understanding.
- Our results indicate that ICT occupations are well-represented in both ESCO and CNL-UWV. However, a significant number of non-ICT occupations also incorporate digital skills. Notably, the distribution of digital skills across occupations varies considerably, with the number of skills per occupation ranging from 2 to 80. In general, ESCO exhibits a higher density of digital skills compared to CNL-UWV.

Despite efforts to enhance the robustness of our methods, we conclude that current skill and occupation datasets lack the necessary level of detail and comprehensiveness to support the development of a fully reliable digital score indicator. It is also important to note that neither ESCO nor CNL-UWV were originally designed for this specific purpose, and the CNL-UWV data used in this study was still in a draft development phase.

If these datasets are to be used for the purpose of scoring digital occupations, several key issues must be addressed:

- Skills are described at varying levels of granularity. For example, "woodworking" may be treated as a single skill or decomposed into sub-skills such as sawing, drilling, and sanding. This lack of uniformity can significantly complicate cross-occupation comparisons.
- Some skills are explicitly listed for one profession but considered implicit in another, thereby reducing overall comparability across roles. We propose that incorporating education level into the scoring function could potentially mitigate some of these issues, an area warranting further investigation in future research.
- Large variations in the number of skills across occupations within the same group may significantly affect the digital scores generated by the first two methods.

We should mention that skill ontology based indicators, have important advantages over survey-based indicators. They provide a more structured and consistent description of skills, while survey-based measures can lack detail about tasks and skills and may be affected by biases from self-reported responses.

In conclusion, current skill and occupation datasets are not yet sufficiently detailed or comprehensive to support the development of a fully reliable digital score indicator. Finally, while ESCO and CNL-UWV each have distinct strengths and limitations, their integration could contribute to more coherent policymaking and enhance understanding of the digital transformation of occupations.

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Appendix A 'ICT' occupations within CNL-UWV and Non-digital terms

Table A1: Occupations including 'ICT' in the label.

1	ICT managers (general)
2	ICT managers (management)
3	ICT managers (development)
4	ICT project leaders
5	ICT geo-information systems
6	ICT systems designers and analysts
7	ICT testers and test managers
8	ICT security specialists
9	ICT specialists (hardware)
10	ICT workplace administrators
11	ICT helpdesk employees and user support staff

Tabel A2: Non-digital terms

Administer
Mathematical models
File
Prepare documents
Develop architectural drawings
Scientific
Graphics
Data typing
Format documents
Information analysis
Prepare models
Prepare reports
Analyze sales results
Frequently maintain documentation
Teach university courses

Appendix B Concordance coefficient

In section 4.2 we presented results on rating digital skills in high, medium or low complexity by different project members. Below we calculated the concordance coefficient Light's Kappa. The results are given in Table B1. We observe in both data sets Fair agreement. Table B2 shows the interpretation of Kappa.

Table B1: Concordance coefficient Light's Kappa

	CNL-UWV	ESCO
Subjects	294	1175
Raters	4	4
Kappa	0.307	0.341
p-value	3.47e-05	0

Table B2: The value of Kappa strength of agreement

1	< 0	Poor
2	0.01 - 0.20	Slight
3	0.21 - 0.40	Fair
4	0.41 - 0.60	Moderate
5	0.61-0.80	Substantial
6	0.81 - 1.00	Almost perfect

Even among experts, subjective interpretation plays a role in complexity classification. In general this level of disagreement suggests the need for clearer rating guidelines, or perhaps better understanding of complexity of digital tasks.

Appendix C Calculating digital scores for different occupations from CNL-UWV

Here we calculate digital scores for three different occupations following three methods from section 4.3.

'ICT system developers and analysts'

Table C1 shows identified digital skills and assigned complexity levels (Mode) for occupation 'ICT system developers and analysts' in CNL-UWV.

Table C1: Skills for 'ICT system developers and analysts'

	Skill	Type	Digital	Mode
1	Determine adjustments to information systems	Optional	1	3
2	Analyze the architecture of information systems	Essential	1	3
3	Design the architecture of information systems	Optional	1	3
4	Analyze business processes	Optional	0	0
5	Lead functional and technical research on the architecture of information systems	Optional	1	2
6	Determine functional solutions	Essential	0	0
7	Determine user needs for ICT	Essential	1	2
8	Determine ICT strategies	Essential	1	3
9	Develop ICT applications	Essential	1	3
10	Analyze customer questions	Essential	0	0
11	Present prototypes for validation	Optional	0	0
12	Analyze technical problems	Essential	0	0
13	Draft technical specifications	Optional	0	0
14	Draft test procedures for information programs and applications	Essential	1	2
15	Check achieved performance	Optional	0	0

We have 15 skills in total, from these 8 are essential and 7 are optional. Of the essential skills 5 are digital and of the optional skills 3 are digital. We can calculate the digital scores according to three methods we have define in section 4.3:

$$\text{Weighted sum score} = \frac{1}{8}\sum_{j}^{8} w_j + 0.5\frac{1}{7}\sum_{j}^{7} w_j = \frac{5}{8} + 0.5\frac{3}{7} = 0.84;$$

$$\text{Mode of complexity score} = \frac{1}{8}\sum_{j}^{8} \text{mode}_k(w_{jk}) + \lambda\frac{1}{7}\sum_{j}^{7} \text{mode}_k(w_{jk})$$
$$= \frac{1}{8}(3+2+3+3+2) + \lambda\frac{1}{7}(3+3+2) = 2.20;$$

$$\text{Highest rank score} = \max_{j\in ess}\{\text{mode}_k(w_{jk})\} = 3.$$

'Accountants'

Table C2 shows identified digital skills and assigned complexity levels (Mode) for occupation digital skills and assigned complexity levels for occupation 'Accountants' in CNL-UWV.

	Skill	Type	Digital	Mode
1	Draft recommendations	optional	0	0
2	Coordinating team activities	optional	0	0
3	Forwarding audit elements	essential	0	0
4	Preparing audit reports	optional	0	0
5	Conducting audits	optional	0	0
6	Preparing audits	essential	0	0
7	Identifying business risk management tools	optional	0	0
8	Optimizing accounting control processes	essential	1	1
9	Performing accounting audits	essential	1	1
10	Determining accounting procedures	essential	1	1
11	Analyzing budgetary deviations	optional	0	0
12	Monitoring the economic cycle	optional	0	0
13	Identifying economic value	optional	0	0
14	Developing own expertise	essential	0	0
15	Providing expertise in projects and mergers and acquisitions	optional	0	0
16	Communicating externally	essential	0	0
17	Preparing financial reports	optional	0	0
18	Assessing financial risks	optional	0	0
19	Monitoring the financial condition of organizations	essential	0	0
20	Providing technical support to clients in mergers and acquisitions	optional	0	0
21	Advising companies on their development strategy	optional	0	0
22	Monitoring organizations in difficulties	optional	0	0
23	Reporting	essential	0	0
24	Establishing reorganization procedures	optional	0	0
25	Identifying risks in corporate policy	optional	0	0
26	Creating a structure for internal audits	optional	0	0
27	Verifying the application of accounting control processes	essential	1	2
28	Maintaining professional documentation	essential	0	0

Tabel C2: Skills for 'Accountants'

We have 28 skills in total, from these 11 are essential and 17 are optional. Of the essential skills 4 are digital and of the optional skills none are digital. Modes of these skills are given in the last column of the table. We can calculate the digital scores according to three methods we have define in section 4.3:

$$\text{Weighted sum score} = \frac{1}{11}\sum_{j}^{11} w_j + 0.5\frac{1}{17}\sum_{j}^{17} w_j = \frac{4}{11} + 0.5\frac{0}{17} = 0.5;$$

$$\text{Mode of complexity score} = \frac{1}{11}\sum_{j}^{11} \text{mode}_k(w_{jk}) + \lambda\frac{1}{17}\sum_{j}^{17} \text{mode}_k(w_{jk})$$
$$= \frac{1}{11}(1+1+1+2) + \lambda\frac{1}{17}(0) = 0.625;$$

$$\text{Highest rank score} = \max_{j\in ess}\{\text{mode}_k(w_{jk})\} = 2.$$

'Firefighters'

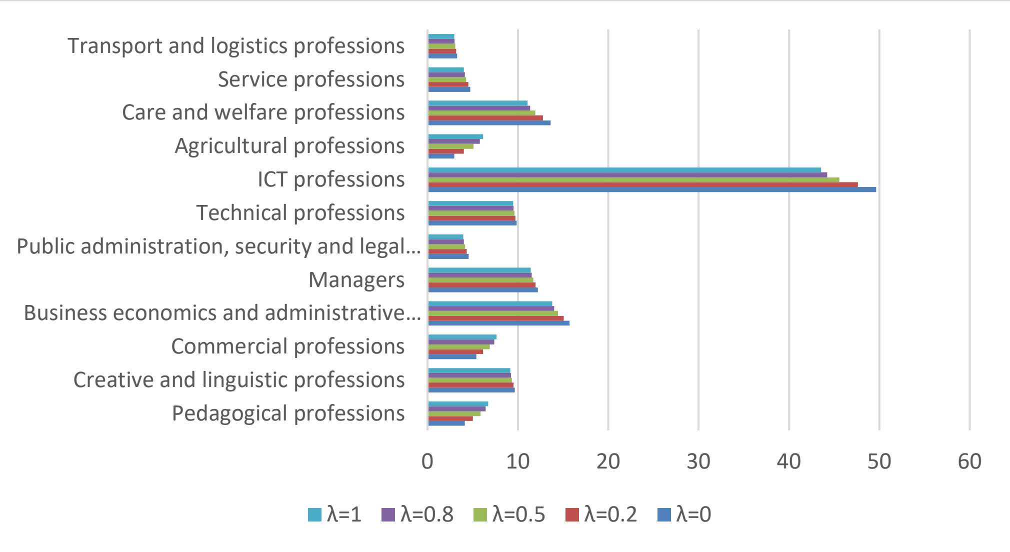
We could not identify digital skills among the listed skills for occupation 'firefighters'. Hence according to methods in section 4.3 the digital score for this occupation is 0.

Tabel C3: Skills and digital scores

	Skill	Type	Digital	Mode
1	Inform stakeholders about interventions, risks, and developments	essential	0	0
2	Raise awareness of prevention, safety, and first aid actions and techniques	optional	0	0
3	Fight fires and explosions	essential	0	0
4	Warn the public	optional	0	0
5	Rescue animals in distress	optional	0	0
6	Provide urgent medical assistance	optional	0	0
7	Conduct gas measurements (ex-ox-tox)	optional	0	0
8	Maintain tools or equipment	optional	0	0
9	Provide help and assistance	essential	0	0
10	Provide logistical support	optional	0	0
11	Demarcate accident or disaster areas and determine interventions	optional	0	0
12	Check public places for (fire) safety and permits	optional	0	0
13	Evaluate risk situations	essential	0	0
14	Combat released environmentally hazardous substances	optional	0	0
15	Arrange water supplies	optional	0	0
16	Conduct searches for missing persons	optional	0	0

Appendix D Different values of λ

Figure D1: Weighted sum digital score for CNL-UWV on BRC level.



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