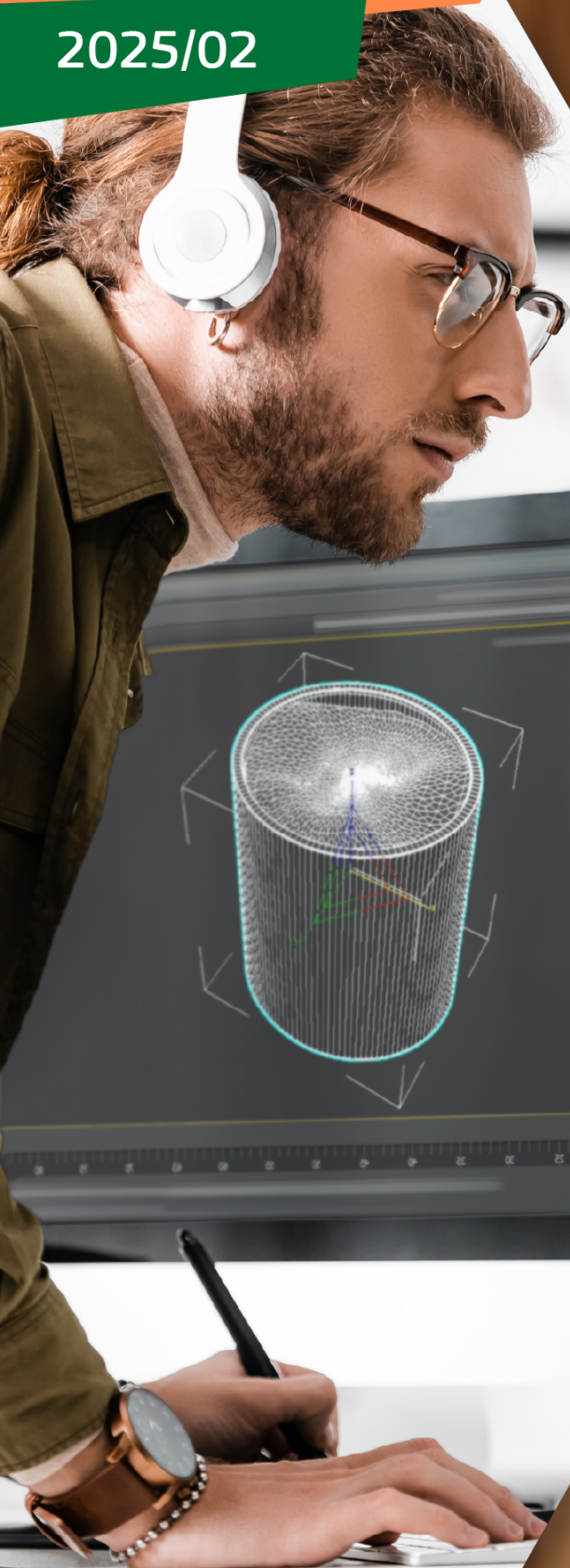


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Digital skills in Europe:
a methodological and
empirical assessment

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Digital skills in Europe: a methodological and empirical assessment

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Introduction

Digitalization is one of the major drivers of change in labour markets. By empowering process and organizational innovations, digital technologies may reshape how production processes are organized, tasks are carried out, information is shared, and decisions are made. At the same time, the adoption of digital technologies is linked to the availability of an appropriate skill base.

To maximize productivity gains and the economic benefits related to digital technologies, individuals (and organizations) need to update and mobilize their digital skills. This makes digital skills endowment of an economy a key predictor of its capacity for technological innovation, which in turn underpins its competitiveness and growth potential.⁴ Conversely, digital skill shortages may prove to be a major constraint on economies' ability to grow and stay on the technological frontier.

As digitalization unfolds, not everyone is likely to benefit equally, however. Digital skills are not distributed evenly across and within countries, across population groups, and across occupations and sectors of the labour markets. Digital skills are expected to be relatively more concentrated in high-skilled jobs, high-tech sectors, high-income areas, capital cities and among younger workers. The same goes for the capacity to seize the employment and economic opportunities related to digital technologies. In contrast, a relatively lower digital skill intensity is expected to be found among low-skilled and older workers, as well as in areas characterized by poor innovation and weak propensity to invest.⁵

The importance of digital skills for innovation and growth places them at the centre of attention of both policymakers and researchers. At the EU level, digital skills constitute one of the four priority areas under the 2030 Digital Decade Policy Programme that guides all EU actions related to digital.⁶ More specifically, it sets ambitious targets to ensure that 80% of adults have at least basic digital skills and to reach 20 million Information and Communication Technology (ICT) specialists in employment (balanced by gender) by 2030. A range of policy initiatives have been adopted to support progress towards these goals,⁷ including the development of the DigComp framework by the European Commission to provide a common understanding of digital skills in different competence areas.⁸ The diffusion of artificial intelligence (AI), regarded by many scholars as a 'general-purpose' technology,⁹ will make digital skills even more crucial. This is because the productivity gains that AI is expected to unleash depend on the skills needed to design and develop such technologies; as well as on complementary skills that allow workers and firms to maximize AI's benefits through its use.¹⁰

⁴ State of the Digital Decade 2024: <https://digital-strategy.ec.europa.eu/en/library/report-state-digital-decade-2024>

⁵ Caravella et al. (2023)

⁶ <https://digital-strategy.ec.europa.eu/en/policies/europes-digital-decade>

⁷ For a comprehensive summary of actions taken, see <https://digital-strategy.ec.europa.eu/en/policies/digital-skills-initiatives>

⁸ The latest iteration DigComp 2.2 includes 250 new examples of knowledge, skills and attitudes that help citizens engage confidently, critically and safely with digital technologies, and new and emerging ones such as systems driven by artificial intelligence (AI). For more details, see Vuorikari et al (2022).

⁹ Crafts, N. (2021)

¹⁰ Eloundou et al. (2023)

Recent research has attempted to map the distribution of digital skills (geographically and across population groups) and analyse their impacts.¹¹ While literature has flourished, available evidence is far from conclusive concerning the characteristics, distribution and drivers of digital skill diffusion. Two key factors contribute to this. First, digitalization is a rapidly evolving process, requiring researchers to continuously update definitions and measurement approaches. Second, the growing number of indicators—based on different data sources and methodologies and focusing on different aspects of digitalization—makes it difficult to reconcile findings. As a result, studies relying on different digital skill indicators often yield only partially converging (or even diverging) evidence on the diffusion of such skills.

This paper compares a set of occupation-based indicators measuring digital intensity of work and distils common findings about its distribution in the EU. It starts by providing a comprehensive overview of available occupation-based indicators of digital intensity of work and comparing the methodologies and data used to construct them. It shows that these indicators are rather similar in design, though there are some important differences. It proceeds to compare indicator values by occupation, highlighting that these are broadly similar across available indicators. It then provides a broad mapping of digital intensity of work across different countries and population groups. Finally, the occupation-based indicators of digital intensity are compared to other measures of work digitalisation (worker-reported use of digital skills, occupational exposure to AI) to set them in a broader context.

Measuring digital skills at work

Utilisation of digital skills at work is difficult to measure. Skills are intrinsically complex to quantify. Beyond what can be formally traced by accounting for education levels, professional qualifications or work experience, skills are shaped by individual and organization-specific learning processes. Likewise, country, industry and firm-level heterogeneities may significantly affect the development and use of skills, including digital ones. For instance, the same digital technology may be used in rather different ways across organizations or tasks, leading to heterogeneous learning-by-doing processes and analogously, heterogeneous skill endowments. Therefore, the very nature and economic implications of digital skills may vary substantially across countries, industries, firms and individuals. An additional challenge relates to the limited availability of reliable and fine-grained data capable of capturing some of the complexity and heterogeneity mentioned above.

Thus, empirical evidence on digital skills remains characterized by gaps, with many important research questions left unanswered. Here, it is important to mention two major limitations. First, digital skills are difficult to measure directly and, thus, are often assessed using proxies that fail to capture their full complexity.¹² For example, basic skills sufficient for using simple digital devices are not clearly differentiated from more advanced skills, such as those required for designing or developing new digital technologies.¹³ This means that general assessments of digital skills might overlook important variations in digital performance. Second, there is scarce evidence regarding the supply, demand, and structural factors that influence the spread of digital skills at territorial level, and, related to this, there is insufficient understanding of

¹¹ Guarascio et al. (2025); Bertoni et al (2024); Ciarli et al. (2021)

¹² Castellacci (2020).

¹³ Santoalha et al. (2021)

what drives processes of convergence or divergence across regions.¹⁴ At the same time, the number of indicators on digital skills is growing and new challenges emerge with comparing and eventually reconciling the evidence stemming from different strands of research. For example, in the EU, there exists a diverse range of indicators based on individual- and enterprise-level surveys¹⁵ and occupational skill requirement descriptions.

This paper focuses specifically on comparing indicators of occupational digital intensity, one of the most popular tools to map intensity, distribution and diffusion of digital skills. Even in this case, however, there are several indicators developed by different researchers, which may result in potentially heterogeneous evidence. In what follows, we analyse the methodological characteristics of three major occupational indicators adopted to map digital intensity of work across the EU: the Digital Intensity Index (DII),¹⁶ Digital Competency Index (DCI),¹⁷ and Digital Skills Index (DSI).¹⁸ This review focuses on their data sources, methodological approaches, geographical and time coverage, strengths and limitations. Later in the paper, these indicators are compared to several indicators that measure digital skills at individual level (through the European skills and jobs survey and the EU Labour Force Survey) to provide a broader reflection on their added value.

All these indicators operate at the occupational level and capture digital skill requirements from a detailed, EU-wide occupational skill dictionary. More specifically, they rely on the European Skills, Competences, Qualifications and Occupations (ESCO) dictionary,¹⁹ which provides a detailed mapping of skill requirements by occupation, using skill and occupation definitions that are harmonised across EU Member States. They measure digital intensity by occupational groups defined according to the International Standard Classification of Occupations (ISCO)²⁰ and consistently applied by the EU Member States. Given their reliance on the EU-wide occupational skill dictionary, these indicators are applicable in all EU Member States. When combined with other relevant datasets, such as the EU Labour Force Survey (EU-LFS), the occupational values of these indicators can be aggregated across occupational groups to arrive at broader statistics, including digital intensity of work in a given country or for a given population group. It is important to underline that occupation-based indicators tend to proxy the demand for digital skills for a specific occupation rather than the supply. Nonetheless, such indicators may also partly reflect heterogeneities concerning the supply-side (e.g. ICT-related education and training programs).

The Digital Intensity Index (DII) measures the share of digital skills among all skills required for a given occupation. For each ISCO 3-digit occupational group, it calculates the share of digital work-related skills: if an occupation requires 10 skills and one is digital, the value of the index is 0.1. This may be problematic for occupations with low number of skill requirements, as in this case even a single digital skill may lead to an overestimation of digital intensity. Digital skills

¹⁴ Balland et al. (2021)

¹⁵ E.g. Eurostat's Survey on the use of ICT in households and by individuals, CEDEFOP's European skills and jobs survey, or Eurostat's survey on ICT usage and e-commerce in enterprises.

¹⁶ Barslund, M. (2022) provides a comprehensive summary of the methodology used to produce the first version of this indicator. This has been subsequently refined and updated in European Commission (2023) & European Commission (2022). This paper uses the most recent version of this indicator.

¹⁷ Lennon et al. (2023)

¹⁸ Caravella et al. (2023)

¹⁹ <https://esco.ec.europa.eu/en/about-esco/what-esco>

²⁰ <https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/>

are identified via the DigComp framework,²¹ which is mapped onto the ESCO dictionary to identify skills that can be considered digital. This mapping is done at the level of ISCO 4-digit occupational groups. The DII values are then aggregated to the ISCO 3-digit level using weighted averages, with weights reflecting the number of workers in each ISCO 4-digit group derived from EU-LFS data. Two separate sets of occupational weights are calculated for EU-level analysis (using EU-wide occupational weights) and national-level analysis (using country-specific weights). A rather broad definition of digital skills is adopted, including all skills from the DigComp framework as well as skills linked to working with computers.²²

The Digital Competency Index (DCI) measures the ratio between the share of digital skills in an occupation and the share of digital skills in the whole set of occupations and skills.

A value higher than 1 indicates that, relative to all other jobs, a given occupation is more intensive in use of digital skills. In other words, the DCI proxies the relative 'digital specialization' of each occupation. To do so, the number of digital skills required to perform a given occupation is divided by the total number of skills needed to perform a given occupation (1). Then, the total number of digital skills required to perform all occupations is divided by the total number of skills needed to perform all occupations (2). For a given occupation, the DCI is derived by dividing (1) by (2). Two complementary approaches are followed to identify digital skills from the ESCO dictionary. First, skill groups are selected from the hierarchy of skills whose name contains the terms 'computer', 'ICT', or 'digital' - any skill belonging to at least one of these groups is defined as digital skill. Second, text data is gathered from skill labels and descriptions for all skills and for digital skills as defined in the first approach. Text analysis is then used to identify additional terms that describe digital skills and to classify further relevant skills.²³ The DCI values are calculated at ISCO 5-digit level and then aggregated to ISCO 4- and 3-digit levels by using simple averages across occupational groups. This approach can lead to either underestimation or overestimation of digital skills if the distribution of narrow professions (i.e., ISCO 5-digit) is not uniform within broader occupational groups (e.g., ISCO 3 or 4-digit).

Finally, the Digital Skills Index (DSI) measures digital skill intensity in a given occupation by providing several values accounting for different levels of (digital) complexity: total, practitioners, users and developers. It identifies digital skills in three main steps. First, ESCO occupational descriptors are analysed using textual analysis to identify all skills potentially related to digital technologies, relying on the digital dictionary proposed by Chiarello et al. (2018)²⁴ to identify 75 keywords for digital skills. Second, a dummy variable is defined assuming value 1 if at least one of these 75 keywords (defined in the first stage) matches the description and/or the title of a skill included in ESCO, and 0 otherwise - almost 1,200 'digital skills' are identified in this way, which are used to calculate the total value of the DSI. Finally, each digital skill is then assigned to a category depending on the degree of professional expertise involved, to calculate the other DSI values: 1) user level (309 skills): requiring basic knowledge concerning how to use technology for specific purposes; no specialist expertise needed; 2) practitioner level (348 skills): requiring a certain degree of expertise to tailor technology and adapt it to the use context; and 3) developer

²¹ For more details, see https://joint-research-centre.ec.europa.eu/scientific-activities-z/education-and-training/digital-transformation-education/digital-competence-framework-citizens-digcomp/digcomp-framework_en

²² A version of the indicator that adopts a narrower definition is also available but given that it raises concerns about arbitrary selection of digital skills, it is principally considered as a means of sensitivity analysis. This narrower version of the indicator is not considered in this paper.

²³ Note that several options of the DCI indicator are tested by the authors, all of which are highly correlated. The description here pertains only to the preferred option of the indicator indicated by the authors (Option 3 from the original article). We only retain this option for the subsequent analysis in this paper.

²⁴ Chiarello et al. (2021)

level (546 skills): requiring significant expertise to design and modify technology. The DSI values are calculated at ISCO 4-digit level and aggregated to ISCO 3-digit level using employment weights.

Overall, these indicators provide a comprehensive picture of digital intensity of different occupations, considering their skill requirements in much more detail than other proxies.

By relying on the ESCO dictionary, they consider a fine-grained overview of the contents of occupations (i.e., knowledge, abilities, tasks) to assess their digital intensity. This allows for a precise identification of digital skills and their importance even within narrow occupational groups, which goes beyond traditional proxies of digital skills (such as worker-reported use of digital devices or tools) that provide more generic and sometimes biased measures of digital skill intensity. In fact, some of the indicators of occupational digital intensity even distinguish different types of digital skills by their complexity. When combined with other EU-level datasets that precisely identify occupational categories, such as the EU-LFS, these indicators can provide a good overview of digitalisation of work by EU-Member States, their sub-national regions, and across different population groups. They can also be used to trace developments in digitalisation of work through time.

However, as all the three indicators focus on the occupation-level information, there is a lack of information concerning the individual, firm and sectoral-level dimension. For example, while these indicators can precisely assess the digital intensity of a given occupation, they cannot capture its variation across individuals working in that occupation. In addition, as these indicators are based on occupational descriptions, they do not necessarily cover actual use of digital skills at work nor its frequency. Neither do they cover the digital skills of the unemployed and those outside of the labour force. This calls for additional analysis or, eventually, for the integration of occupation-based measures with variables stemming from different sources that would avoid providing partial or biased representations of digital skills and of their distribution.²⁵ Moreover, some of the sources used to build these indicators – notably the ESCO dictionary and the DigComp framework – require continuous updating²⁶ given the pace of change of digital technologies and related skills. This may increase the risk of obsolescence, weakening indicators' robustness over time.

Finally, the differences in design of the three indicators lead to concerns about comparability of their results. Notably, the indicators vary in their approaches to identifying digital skills, to aggregate values across occupations, and to consider the different levels of complexity of digital skills. This generates concerns about relatively similar indicators yielding different results concerning intensity and diffusion of digital skills and raises questions about the sensitivity of measurement of digital skills to certain methodological choices. This is explored in the next section of this paper.

Comparing indicators of occupational digital intensity

This section empirically compares the DII, DCI and DSI indicators to assess whether different methodological choices taken to construct them lead to significant differences in the digital

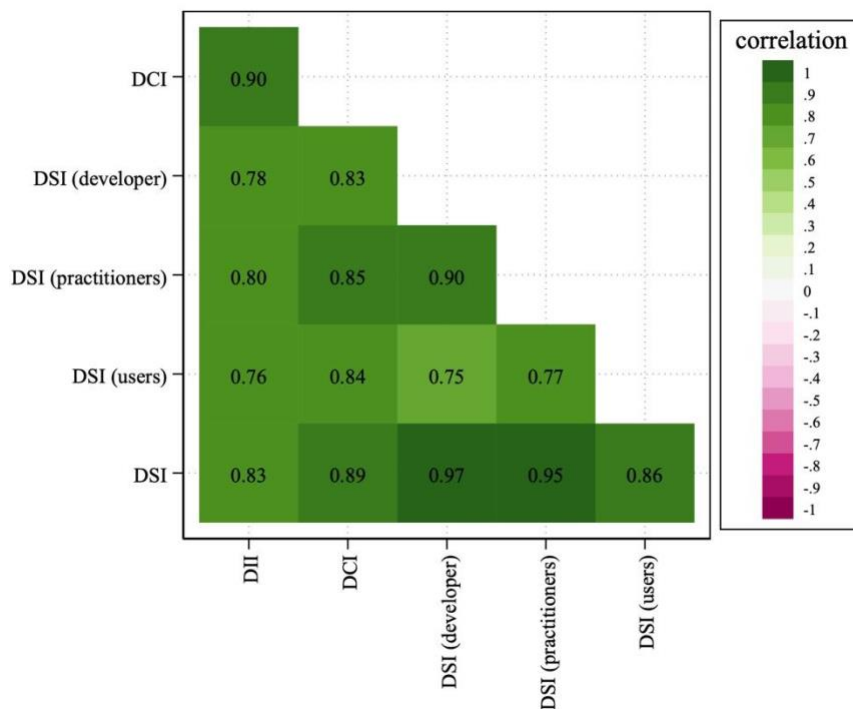
²⁵ For a recent example of digital skills analysis based on individual-level surveys see Bertoni et al (2024).

²⁶ The last update of DigComp (to DigComp 2.2) framework took place in 2022. The next update (DigComp 3.0) is expected to be published by the end of 2025. It will consider skills associated with emerging technologies, focusing on AI; citizen cybersecurity; information and data literacy; misinformation and disinformation; rights, choice and participation; and wellbeing.

intensity of work across occupations. To ensure meaningful comparisons between these indicators, their values are normalized to a range from 0 (no digital content) to 1 (the highest digital intensity).²⁷ The indicator values are first compared by ISCO 3-digit occupational groups and then also by broader ISCO 1-digit occupational groups to check for implications of different ways of aggregating indicator values across indicators.

Correlation analysis shows that these indicators are consistent in capturing digital intensity at occupational level, despite differences in methodological choices. All indicators are strongly, positively correlated across ISCO 3-digit occupational groups (Figure 1), especially the DII and the DCI (correlation coefficient of 0.90). The DSI in all its variants (developer, practitioner, user and total) also exhibits high correlation with the DII and DCI, with coefficients ranging from 0.75 to 0.89.

Figure 1. Pairwise correlations of digital intensity indicators across 3-digit ISCO occupational groups in the EU, 2022



Note: Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

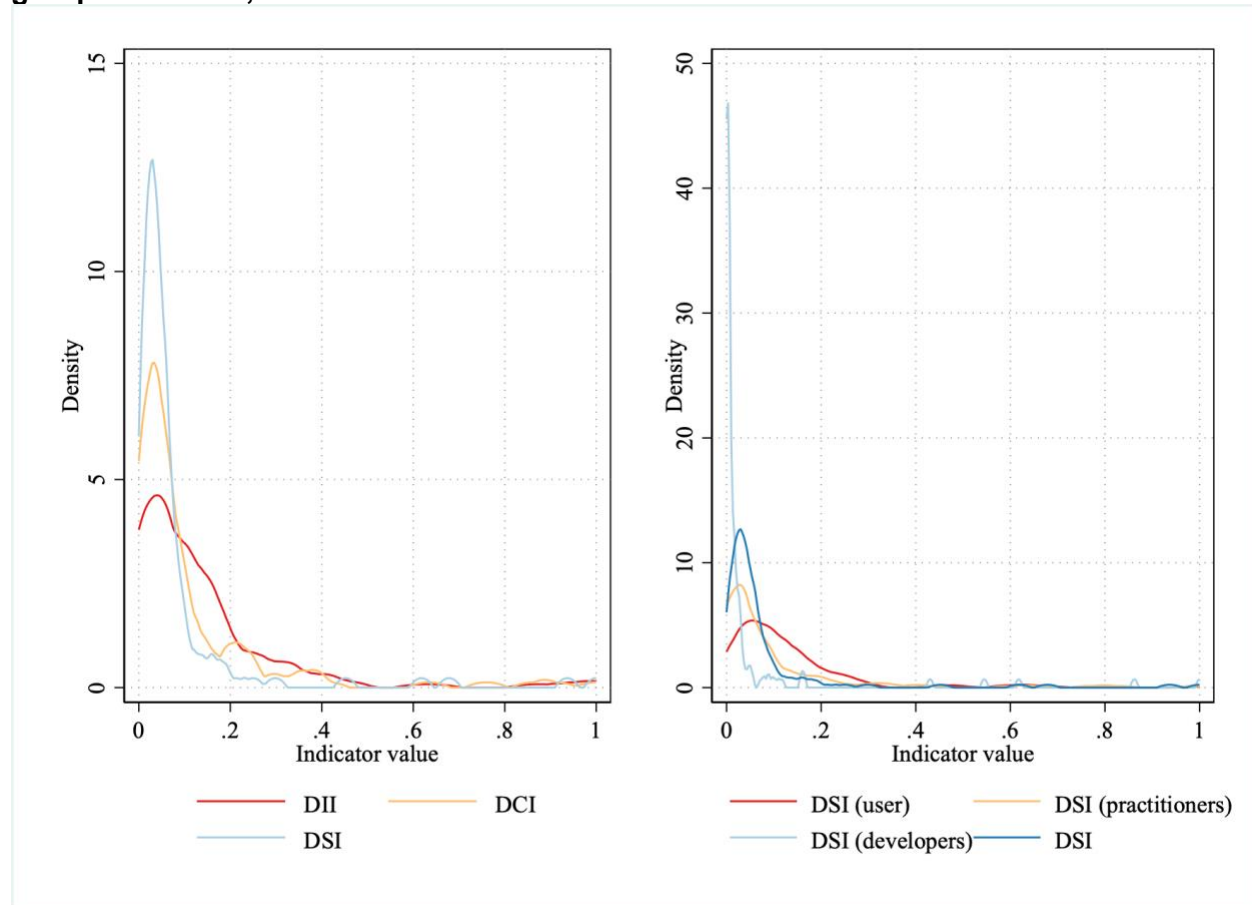
All three indicators show that most occupations have low digital intensity, identifying only a small subset of highly digitally intense ones. This can be seen from Figure 2, which plots the distribution of indicators of digital intensity by their value and is heavily skewed to the right – that is, most occupations have digital intensity below 0.2 regardless of the indicator used. While all three indicators are skewed to the right, this is the most pronounced for the DSI. To better understand this, the right-hand graph provides a breakdown of the DSI into its components (user, practitioner, and developer). The results show that the right-skewness primarily arises from the

²⁷ Min-max normalization was applied to rescale the indicator values to a range between 0 and 1. The formula used is $(X - X_{\min}) / (X_{\max} - X_{\min})$, where X is the original value, while X_{\min} and X_{\max} are, respectively, the minimum and maximum values of the indicator.

distribution of advanced digital skills captured by the developer variant, where most occupational values are close to zero. Basic user skills captured by the user variant are more widespread, contributing to a broader, flatter distribution curve.

The top 15 most digitally intense occupations according to DII, DCI and DSI overlap to a large extent, with more than half of the occupations like software developers, ICT managers and data analysts consistently appearing across all three indicators (Table 1). This underscores the consistency of these indicators in capturing digitalisation at the occupational level. Interestingly, we also find occupations which are not directly associated with digital knowledge and technologies (e.g., librarians, secretaries, keyboard operators) but whose activities are increasingly carried out relying on digital tools. In fact, the DSI, which aggregates user, practitioner and developer skills, tends to provide a somewhat more comprehensive view by capturing a greater range of digital competencies within each occupation. This approach might cause certain occupations, such as engineering professionals, to rank higher in DSI compared to DII or DCI.

Figure 2. Distribution of digital intensity indicators across 3-digit ISCO occupational groups in the EU, 2022



Note: Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

Interestingly, certain occupations only appear in the top 15 for one of the digital indicators. For instance, the inclusion of blacksmiths, toolmakers and related trades workers among the most digitally intensive occupations in the DSI appears counterintuitive at first glance. This raises an important question: 'Does this reflect the pervasiveness of digital transformation in traditional

roles, or could it be due to how digital skills are defined across indicators?'. We argue that the latter is more likely. The definition and classification of digital skills likely play a crucial role in explaining these differences in rankings. For example, in occupations with relatively few skill requirements, such as blacksmiths, toolmakers and related trades workers, even a single skill being classified as digital in one framework but not in another can significantly influence the indicator value. This could account for why certain occupations appear in the rankings of one indicator but not others. Finally, some new occupations that one would have expected to find in the list (e.g., digital content creators) are not there yet as the pace of digitalization tends to be faster than the periodical update of statistical classifications such as the ISCO.

Table 1. Top 15 occupations by digital intensity indicators

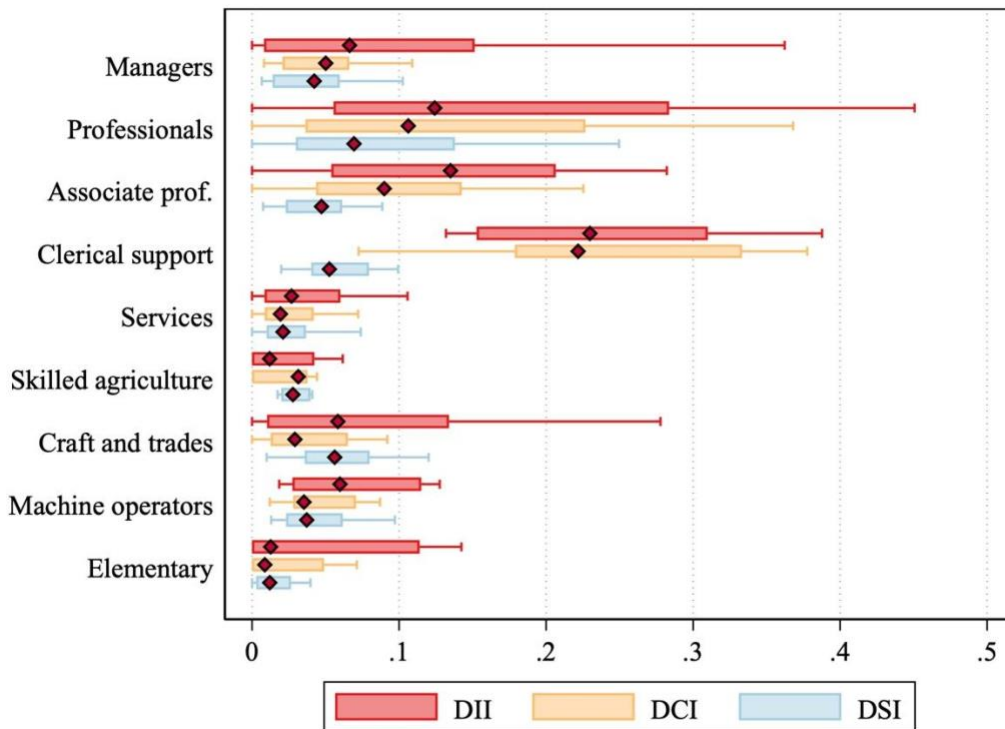
DII	DCI	DSI
351 - ICT operations and user support technicians	252 - Database and network professionals	252 - Database and network professionals
252 - Database and network professionals	251 - Software and applications developers and analysts	251 - Software and applications developers and analysts
251 - Software and applications developers and analysts	351 - ICT operations and user support technicians	351 - ICT operations and user support technicians
352 - Telecommunications and broadcasting technicians	413 - Keyboard operators	133 - ICT service managers
262 - Librarians, archivists and curators	133 - ICT service managers	215 - Electrotechnology engineers
212 - Mathematicians, actuaries and statisticians	352 - Telecommunications and broadcasting technicians	413 - Keyboard operators
431 - Numerical clerks	412 - Secretaries (general)	216 - Architects, planners, surveyors and designers
215 - Electrotechnology engineers	212 - Mathematicians, actuaries and statisticians	742 - Electronics and telecommunications installers and repairers
133 - ICT service managers	215 - Electrotechnology engineers	212 - Mathematicians, actuaries and statisticians
413 - Keyboard operators	262 - Librarians, archivists and curators	732 - Printing trades workers
264 - Authors, journalists and linguists	411 - General office clerks	214 - Engineering professionals (excluding electrotechnology)
421 - Tellers, money collectors and related clerks	221 - Medical doctors	352 - Telecommunications and broadcasting technicians
412 - Secretaries (general)	431 - Numerical clerks	311 - Physical and engineering science technicians
216 - Architects, planners, surveyors and designers	216 - Architects, planners, surveyors and designers	264 - Authors, journalists and linguists
334 - Administrative and specialised secretaries	732 - Printing trades workers	722 - Blacksmiths, toolmakers and related trades workers

Source: Author's elaboration based on indicator values reported in research

Focusing on broad occupational categories shows that managerial, (associate) professional and clerical support work tends to be somewhat more digitally intense (Figure 3). This is true across all indicators, although digital intensity varies considerably within these occupational groups, particularly for the DII. This variability suggests an uneven distribution of digital skills within high-skilled and clerical occupations, with some roles being heavily digitalised and others less so. At the other end of the spectrum, occupational groups with overall low average digital intensity (such as services, skilled agriculture, machine operators and elementary occupations) tend to show much smaller variability in digital intensity, indicating a more uniform distribution of digital skills.

While DII, DCI and DSI show comparable levels of digital intensity across broad occupational groups, there are important differences. A significant difference emerges between the DSI and the other two indicators for clerical occupations. The high scores for DII and DCI suggest that clerical occupations involve a relatively high concentration of digital skills compared to the overall workforce. The lower DSI scores indicate that these jobs likely rely on basic digital skills rather than advanced digital competencies, such as those required by developers or technical specialists, which are more prevalent among professionals.

Figure 3. Distribution of digital indicator values by 1-digit ISCO occupational groups in the EU, 2022



Notes: The box plot displays the distribution of digital indicators by 1-digit ISCO occupations, highlighting the median and interquartile range (IQR), which represents the range between the first quartile (Q1) and the third quartile (Q3). The 'whiskers' extend to the smallest and largest data points within 1.5 times the IQR from the box; Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

Mapping digital intensity of work

Given the consistency of the DII, DCI and DSI in measuring digital occupational intensity, the next logical step is to combine these indicators with data from the EU-LFS to map digital intensity of work for different groups of workers and different EU Member States. The digital intensity of work expresses an average occupational digital intensity value for a certain group of workers (or in a certain country) based on the observed occupational patterns in this group.

Digital intensity of work by worker characteristics

All indicators (DII, DCI and DSI) reveal considerable differences in digital intensity of work across different groups of workers (Figure 4 & A1). The digital intensity of work for different worker groups is obtained by linking occupational digital intensity values for ISCO 3-digit occupations with worker populations by occupation derived from the EU-LFS data for the following groups: gender (men; women); age (20-34; 35-49; 50-64); country of birth (native; foreign-born); level of education (ISCED 0-2; ISCED 3-4; ISCED 5+) and type of contract (permanent; temporary). The group differences are then expressed in terms of relative digital gaps, defined as a percentage difference in digital intensity of work compared to the group of workers whose work is the most digitally intensive. This is calculated separately by each worker characteristic (men; age 20-34; native; tertiary educated; permanent contract). Note that these gaps are calculated as simple differences in (weighted) group averages, rather than attempting to control for different worker characteristics simultaneously. Thus, some of the gaps may be related. For example, higher digital intensity of work among native, rather than foreign-born workers may be partly due to differences in the educational attainment of these groups.

Educational attainment emerges as the most significant divide in digital intensity of work. Specifically, workers with lower (upper) secondary education have digital skills that are 60% to 70% (35 to 45%) lower than those with tertiary education. These gaps in digital intensity of work are somewhat less pronounced in DSI than in DCI and DII.

Gender disparities are also notable. Men consistently score higher than women across all three digital indicators, with the most pronounced gap observed in the DSI, which shows that men's work is, on average, 40% more digitally intense than women's. This suggests that men are more often employed in occupations that require at least some digital skills. Such heterogeneity could be driven by the fact that DSI places more emphasis on advanced digital skills (e.g. developer skills) that are linked to STEM occupations known to be gender imbalanced. This approach might cause certain occupations, such as engineering professionals, to rank higher in DSI compared to DII or DCI.

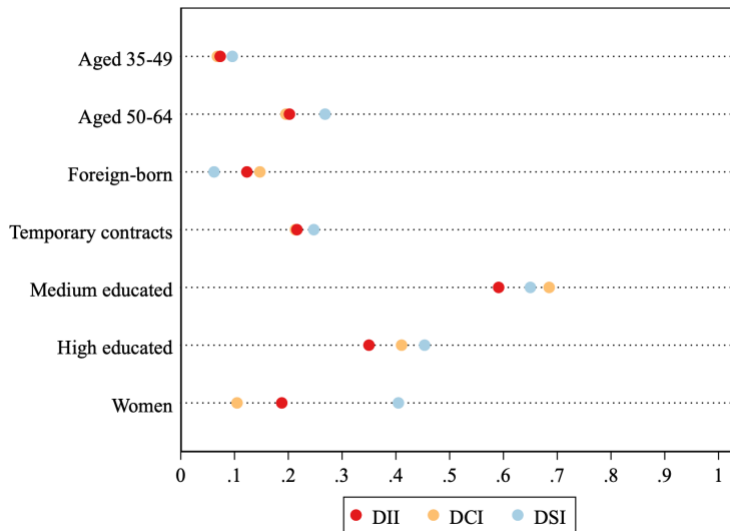
There is a generational divide in digital intensity of work, notably between the youngest and the oldest workers. Young workers aged 20-34 have the highest DSI, DCI and DII scores across all indicators. As age increases, digital intensity of work declines, with workers aged 50-64 engaging in, on average, 20% to 30% less digitally intense work than their younger counterparts.

Workers with permanent contracts have more digitally intense work compared to those with temporary contracts according to all indicators. This gap can be partly attributed to the stability and continuity of permanent employment relationships, which seems to be more conducive to digital skill development. Permanent employees are more likely to have access to

training and professional development opportunities, while temporary workers may face limited access to such resources, as employers might be less inclined to invest in their training.²⁸

Finally, native-born workers tend to work in somewhat more digitally intensive jobs than foreign-born workers (by about 5 to 15%). This reflects lower prevalence of high-skilled occupations among foreign-born, which may be linked to lower levels of educational attainment, challenges with qualifications recognition and/or language barriers.²⁹

Figure 4. Digital gaps (% difference in average digital intensity of work compared to the most digitally intensive group) in the EU, 2022



Note: The group of workers whose work is the most digitally intensive, separately by each worker characteristic: men; age 20-34; native; tertiary educated; permanent contract. Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia
Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

Digital intensity of work by EU Member State

DII, DCI and DSI values vary considerably across EU Member States. This can be seen in Figure 5, which maps the distribution of digital indicators across European countries. The national digital intensities of work have been obtained by linking the ISCO 3-digit occupational values of DII, DCI and DSI with the numbers of workers working in these occupations at the national level derived from the EU-LFS.

All three indicators show a digital divide between the North (and to some extent also West) and the South-East EU. Several northern and western countries (Estonia, Finland, Ireland, the Netherlands and Sweden) consistently show the highest digital intensity of work. In contrast, some south-eastern countries, including Italy, Greece, Hungary and Romania, score low across all indicators. This distinction between the digitally advanced core and the lagging periphery reflects structural differences across countries, including sectoral specialisation, educational attainment, technological capabilities, digital infrastructure and institutional settings.³⁰ For example, countries with a greater concentration of employment in knowledge-intensive services are more likely to

²⁸ Kleinknecht, A. (2020), Reljic et al. (2023)

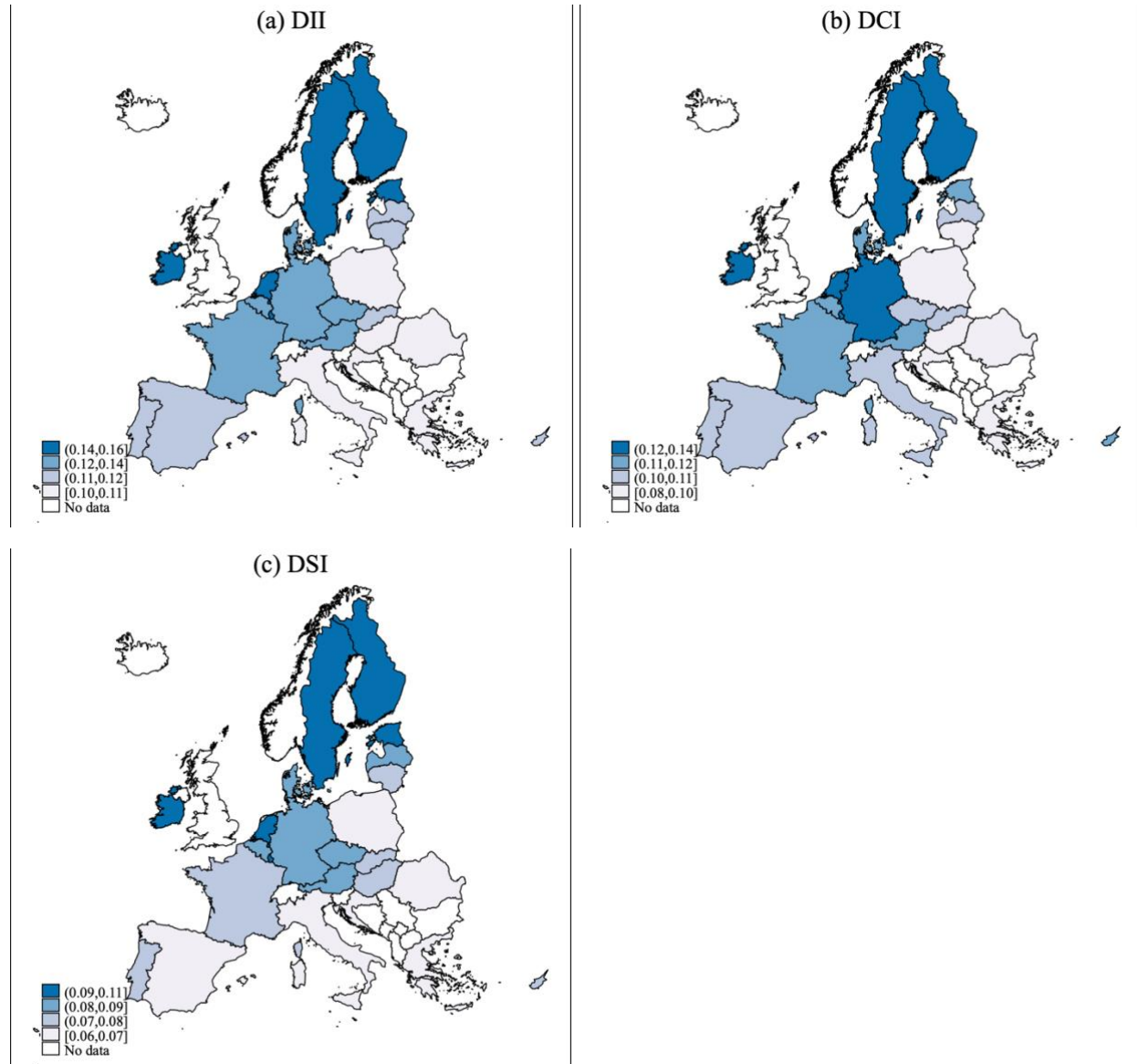
²⁹ European Commission (2023)

³⁰ Xiao and Boschma (2023), Guarascio et al. (2024)

exhibit higher levels of digital skills, as these jobs inherently demand and cultivate advanced digital competencies.

However, despite similarities, DII, DCI, and DSI exhibit some geographical heterogeneity. While DII is highest in the North, DCI is more ‘evenly’ distributed, with countries like France and Germany scoring relatively higher despite their moderate DII. Southern and Eastern Europe generally lag across all three indicators, but differences exist within these regions: Croatia, Poland, Romania, and Greece consistently rank at the bottom, whereas the position of Spain and Hungary depends on the indicator used.

Figure 5. National averages of digital intensity indicators across the EU, 2022



Note: Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

Comparing occupational digital intensity to other measures of work-related digital skills

Besides mapping digital intensity of work across the EU, this paper aims to compare occupational digital intensity (DII, DCI and DSI indicators) to two other measures of work-related digital skills: a) the use of digital tools and skills at work reported by workers via surveys; b) occupational exposure to artificial intelligence (AI) technologies (as a proxy for AI-related skills and competencies). These broader comparisons are important to understand whether occupational digital intensity can, at least partially, capture some other aspects of digitalisation of work, or whether these aspects need to be measured separately.

Occupational digital intensity and worker-reported use of digital skills and tools

This section relies on the following recent measures of worker-reported use of digital skills and tools based on EU-wide surveys:

1. **The proportion of workers reporting they do certain digital activities at work** (using digital devices for work; using internet; using specialised software; programming; developing IT systems; and managing databases) in the European skills and jobs survey (ESJS) carried out in 2021.³¹
2. **The proportion of workers who report spending at least half of their time working on digital devices** in their main or last job in the job skills ad-hoc module of the 2022 EU Labour Force Survey (EU-LFS).³²

While the ESJS indicators provide more granular information about different digital activities at work, the sample of the survey is relatively small, with results only available for broad occupational groups at ISCO-08 one-digit level. The EU-LFS data can be disaggregated at ISCO-08 three-digit level but provides no information on use of specific digital skills or tools by workers. The analysis therefore starts by correlational analysis of occupational digital intensity and worker-reported digital activities for broad occupational groups (ISCO-08 one digit), and then proceeds to more detailed comparisons for narrower occupational groups (ISCO-08 three digit) specifically for use of digital devices reported in the EU-LFS.

Occupational digital intensity closely reflects the prevalence of basic digital activities in broad occupational groups. Table 2 shows high and significant correlation (coefficient close or above 0.8) of DII and DCI with use of digital devices, use of internet and use of occupation-specific software in broad occupational groups. Similar, but somewhat weaker pattern can be observed overall DSI and its version focusing on basic users of digital technologies. The DSI focusing on practitioners and developers has a weaker relationship with basic digital activities since they focus on capturing more advanced digital skills and competencies.

³¹ For more information, see <https://www.cedefop.europa.eu/en/tools/european-skills-jobs-survey/data>.

³² For more information, see https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_modules&oldid=543984#Overview_of_the_modules. More specifically, the workers were asked about the time spent working on digital devices in their main or last job, with the following possible responses: none of the working time, little of the working time, some of the working time, half of the working time or slightly more, all or most of the working time.

Table 2. Pairwise correlations of occupational digital intensity with self-reported digital activities at work across 1-digit ISCO occupational groups in the EU, 2022

	DII	DCI	DSI total	DSI user	DSI practic	DSI develop
<i>Broad digital skills and tools</i>						
Use of digital devices (EU-LFS)	0.8967*	0.8831*	0.6928*	0.8221*	0.6777*	0.4953
Using digital device (ESJS)	0.8673*	0.8223*	0.7295*	0.8577*	0.7034*	0.5310
Using internet (ESJS)	0.8359*	0.8145*	0.7194*	0.7769*	0.7108*	0.5464
Using specialised software (ESJS)	0.7955*	0.7705*	0.6446	0.7321*	0.6398	0.4711
<i>Specific & advanced digital skills</i>						
Managing databases (ESJS)	0.6507	0.6209	0.5616	0.5456	0.5825	0.4395
Developing IT systems (ESJS)	0.2589	0.2618	0.4879	0.2158	0.5460	0.4804
Programming (ESJS)	0.3853	0.3683	0.6678*	0.2737	0.7266*	0.6793*

Note: Statistical significance at $p < 0.05$ indicated by *

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

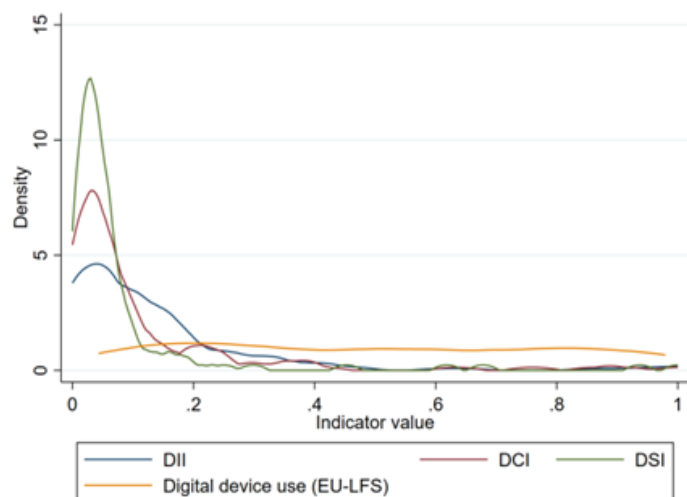
The link between occupational digital intensity and worker-reported basic digital activities reflects the fact that both have higher values among managers, (associate) professionals and clerks compared to other occupational groups. Nevertheless, there are also some differences - notably, (associate) professionals, clerks and managers all tend to report similarly high prevalence of digital activities at work, but occupational digital intensity is higher for the first compared to the latter two groups.

The importance of advanced digital skills for certain occupational groups can get lost when measuring the overall digital intensity of work. Occupational digital intensity based on all digital skills requirements correlates weakly, mostly insignificantly, with reported levels of engagement in programming or IT system development at work by occupation (Table 2). The only exception is the significant correlation between DSI, especially in its practitioner and developer variants that aim to capture more advanced digital competencies, and programming. Occupational digital intensity and database management are positively, but non-significantly, correlated. Thus, while digital occupational intensity closely follows the prevalence of widespread digital activities by broad occupational groups, this is not necessarily the case for narrower, specialised digital activities such as development of IT systems.

Zooming on narrower occupational groups, the occupational digital intensity provides a more accurate picture of work digitalisation than prevalence of basic digital activities. At ISCO 3-digit level, the correlation coefficients of occupational digital intensity and the share of workers who spend at least half of their time working on digital devices are about 0.6 for DII and DCI and 0.4 for DSI (all of them statistically significant). In other words, these measures remain linked, but the link becomes considerably weaker than for broader occupational groups. This is largely because highly digitally intensive occupations involve specialist work requiring multiple advanced digital skills and competencies that go beyond the simple use of digital devices at work. In fact, the share of workers who spend more than half of their working time on digital devices (i.e. the digital device use as measured in EU-LFS) is rather evenly distributed across all occupational groups, as can be seen from Figure 6. In contrast, occupational digital intensity is low for most jobs, but it reaches much higher values for a narrow group of specialist occupations that require multiple digital skills. It would be interesting to explore how occupational digital intensity relates to prevalence of other (more advanced) digital work activities across narrow

occupational groups, but unfortunately the data on advanced digital activities is not sufficiently granular.

Figure 6. Comparison of distribution of digital device use (EU-LFS) and digital intensity indicators across 3-digit ISCO occupational groups in the EU, 2022



Note: Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research (occupational digital intensity) and the 2022 ad hoc module of the EU-LFS 2022 (digital device use).

Overall, occupational digital intensity corresponds with worker-reported prevalence of digital activities across broad occupations but provides a more accurate view of digital intensity of work for specific jobs. Occupational digital intensity is closely linked to basic digital work activities when focusing on broad occupational aggregates. This makes sense, since digitally intense occupations typically involve at least some basic digital activities, such as using digital devices, the internet or some kind of work-related software. However, this link becomes weaker when digging deeper, be it in terms of more specific digital activities or narrower occupational groups. In the first case, this is because measures of occupational digital intensity tend to capture a wide range of digital skill requirements, and thus may not reflect occupational differences in certain specialist digital activities. In the second case, the data collected from workers on prevalence of digital activities at work remains sparse for narrower occupational groups. The only data available at sufficiently granular level relates to the use of digital devices, which does not allow for a precise identification of digitally intensive jobs.

Occupational digital intensity and occupational exposure to AI technologies

Measuring occupation-level exposure to AI technologies is not straightforward. While several indicators have been proposed, the most widely used are those developed by Felten et al. (2021) and Webb (2020).³³ This section relies on the AI-exposure index proposed by Felten et

³³ Despite its broad adoption, this indicator has notable limitations. As discussed in Guarascio et al. (2025), its main weakness is its reliance on crowd-sourced opinions about the overlap between workplace abilities and AI applications. Instead of measuring actual AI adoption, it estimates which occupations, industries and regions are most likely to be affected by AI advancements. Notwithstanding this limitation, AIOE has an almost perfect correlation with a measure recently proposed by Marguerit (2024) that is more closely linked to AI adoption, based on AI-related questions from Stack Overflow that reflect real-world challenges faced by developers, providing reassurance about its reliability.

al. (2021), which is based on the O*NET repertoire³⁴ linking various AI applications - abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modelling, translation, speech recognition and instrumental track recognition - to 52 workplace abilities (j) (e.g., mathematical reasoning, speech recognition, written comprehension, originality, body coordination). Occupational exposure to AI is constructed by weighting the ability-level exposure to AI (A_j) with their prevalence (L_{jk}) and importance (I_{jk}) within each occupation (k):

$$AIOE_k = \frac{\sum_{j=1}^{52} A_j * L_{jk} * I_{jk}}{\sum_{j=1}^{52} L_{jk} * I_{jk}}$$

There is only a weak link between occupational digital intensity and occupational exposure to AI technologies. The pairwise correlations between AI occupational exposure and the DII, DCI and DSI (Table 3, line 4) are modest (from 0.3 to 0.43) and only weakly significant. This weak correlation is also apparent when comparing the list of most digitally intense and most AI exposed occupations. Only two occupations—Software and Applications Developers and Analysts and Mathematicians, Actuaries, and Statisticians—consistently rank high across both AI exposure and digital intensity indicators.³⁵

Table 3. Pairwise correlations of digital intensity and AI exposure indicators across 3-digit ISCO occupational groups in the EU, 2022

Variables	(1)	(2)	(3)	(4)
(1) Digital intensity index (DII)	1.000			
(2) Digital competencies index (DCI)	0.904*	1.000		
(3) Digital skills index (DSI)	0.830*	0.887*	1.000	
(4) AI exposure	0.433*	0.424*	0.296*	1.000

*Note: Statistical significance at $p < 0.05$ indicated by *; Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia*

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

Thus, AI exposure seems to be a particular aspect of digitalisation, one narrowly tied to the integration of AI technologies in the workplace rather than overall digital intensity of work. While digital intensity tends to be higher in ICT-related occupations—such as software developers, database and network professionals, and telecommunications technicians—AI exposure follows a different pattern. Indeed, some argue that AI affects specific cognitive abilities or tasks within occupations, such as speech recognition, mathematical reasoning, or data analysis.³⁶ As a result, occupations highly exposed to AI technologies turn out to be rather specific³⁷ and less widespread compared to those that rank high on digital-skill indicators—at least for now.

This distinction is evident when comparing AI exposure with digital skill measures. Whereas highly digital-intensive occupations, such as ICT technicians and engineers, rely heavily on digital competencies, AI exposure extends to occupations where AI is more relevant for

³⁴ The O*NET repertoire is the US's primary source of occupational information. The O*NET database contains information on hundreds of standardized and occupation-specific descriptors. The database is continually updated by surveying a broad range of workers from each occupation.

³⁵ Guarascio et al. (2025).

³⁶ Felten et al. (2021)

³⁷ See, for example, Hui et al. (2023).

supporting analytical, content creation and problem-solving tasks. For example, legal and finance professionals, university teachers, and journalists are among the most exposed to AI, despite not necessarily ranking high in digital intensity.

Furthermore, the weak link between occupational digital intensity and AI exposure can be attributed to methodological differences in how these indicators are constructed. An important difference concerns the fact that while AI exposure indicators are inherently forward-looking (i.e., focusing on the potential diffusion/impact of AI technologies across occupations), the digital intensity ones capture the actual skill contents/requirements of professions. Overall, this task-based, granular focus contrasts fundamentally with the occupational digital intensity indicators reviewed in this paper, which are skill-based rather than task-oriented.

Conclusions

This paper highlights occupational digital intensity as a robust, accurate and granular measure of digital skills in the EU labour market. Despite their methodological differences, indicators of digital occupational intensity paint a consistent picture of digital skill diffusion across the EU labour market. Digitally intense work is concentrated in a small number of specialist occupations that revolve around advanced digital skills, such as software developers, ICT managers or data analysts. In most other jobs some digital skills are required, but usually account for a relatively modest share of job content. Focusing on occupational digital intensity allows precise identification of digitally intense occupations, a key added value compared to measures focusing on prevalence of (basic) digital activities at work reported by workers in EU-wide surveys.

Mapping occupational digital intensity across the EU shows a digital divide between the North-West and the South-East EU, with digitally intense work most common in several northern and western Member States. There are also important differences across different groups of workers – average digital intensity of work increases sharply with worker educational attainment and there is also some evidence of more digitally intense work among men (compared to women), young workers (compared to older ones) and those with permanent contracts (compared to less stable working arrangements). Further research is needed to understand what drives these differences. Overall, our findings support the need for targeted policy interventions to foster work-related digital skills, both from geographic and demographic points of view.

There remains ample scope to further refine the measurement of digital intensity of work. Firstly, occupation-based indicators primarily focus on demand for digital skills at occupational level. They need be complemented by individual-level data to show differences in digital intensity of work within occupations, or to estimate the overall digital skill supply that includes those not in employment. While there are surveys that collect such data in the EU context, they are either based on relatively small samples of population or only collect information on selected (typically basic) digital activities. Secondly, while digital occupational intensity provides a comprehensive picture of the diffusion of digital skills overall, this may differ considerably from the diffusion of certain specialist digital skills (such as programming or competence with AI technologies). These advanced skills are often concentrated in a particular set of occupations and evolve rapidly with technological and industry changes, whereas occupation-based indicators are slow to update. For instance, AI-related expertise is expanding across finance, legal services, and creative industries, yet these shifts are not yet reflected into occupational classifications. As a result,

relying solely on occupation-based indicators risks underestimating both the pace and scope of technological change in the labour market. Accurately tracking such specialist competencies requires dedicated indicators designed for this purpose.

References

- Balland, P. A., & Boschma, R. (2021). Mapping the potentials of regions in Europe to contribute to new knowledge production in Industry 4.0 technologies. *Regional Studies*, 55(10-11), 1652-1666.
- Bertoni, E., Cosgrove, J., Pouliakas, K. and Santangelo, G. (2024) What drives workers' participation in digital skills training, European Commission, Seville, 2024, JRC137073.
- Bertoni, E., Cosgrove, J., and Cachia, R. (2024) Digital skills gaps - a closer look at the Digital Skills Index (DSI 2.0), European Commission, Ispra, 2024, JRC140617.
- Barslund, M. (2022). The dynamics of ICT skills in EU Member States, Publications Office of the European Union.
- Caravella, S., Cirillo, V., Crespi, F., Guarascio, D., & Menghini, M. (2023). The diffusion of digital skills across EU regions: structural drivers and polarisation dynamics. *Regional Studies, Regional Science*, 10(1), 820-844.
- Castellacci, F., Consoli, D., & Santoalha, A. (2020). The role of e-skills in technological diversification in European regions. *Regional Studies*, 54(8), 1123-1135.
- Chiarello, F., Fantoni, G., Hogarth, T., Giordano, V., Baltina, L., & Spada, I. (2021). Towards ESCO 4.0—Is the European classification of skills in line with Industry 4.0? A text mining approach. *Technological Forecasting and Social Change*, 173, 121177.
- Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7), 104289.
- Crafts, N. (2021). Artificial intelligence as a general-purpose technology: an historical perspective. *Oxford Review of Economic Policy*, 37(3), 521–536.
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. arXiv preprint arXiv:2303.10130.
- European Commission (2022). Employment and Social Developments in Europe – Young Europeans: employment and social challenges ahead. <https://op.europa.eu/webpub/empl/esde-2024/PDFs/KE-BD-22-001-EN-N.pdf>

European Commission (2023). Employment and Social Developments in Europe – Addressing labour shortages and skill gaps in the EU. <https://op.europa.eu/webpub/empl/esde-2024/PDFs/KE-BD-23-002-EN-N.pdf>

European Commission (2024). State of the Digital Decade 2024. Available at <https://digital-strategy.ec.europa.eu/en/library/report-state-digital-decade-2024>

Felten, E., Raj, M., Seamans, R., 2021. Occupational, industry and geographic exposure to artificial intelligence: a novel dataset and its potential uses. *Strategic Manag. J.* 42 (12), 2195–2217.

Guarascio, D., Reljic, J., & Stöllinger, R. (2025). Diverging Paths: AI Exposure and Employment across European Regions. *Structural Change and Economic Dynamics*, 73, 11-24.

Guarascio, D., Reljic, J., Cucignatto, G., Simonazzi, A., & Celi, G. (2024). Between Scylla and Charybdis: long-term drivers of EU structural vulnerability. *Review of Keynesian Economics*, 1(aop), 1-29.

Kleinknecht, A. (2020). The (negative) impact of supply-side labour market reforms on productivity: an overview of the evidence. *Cambridge Journal of Economics*, 44(2), 445-464.

Lennon, C., Zilian, L. S., & Zilian, S. S. (2023). Digitalisation of occupations Developing an indicator based on digital skill requirements. *PloS one*, 18(1).

Marguerit, D. (2024). ‘Augmenting or automating labor? The effect of AI exposure on new work, employment, and wages’.

Reljic, J., Cetrulo, A., Cirillo, V., & Coveri, A. (2023). Non-standard work and innovation: evidence from European industries. *Economics of Innovation and New Technology*, 32(1), 136-164.

Santoalha, A., Consoli, D., & Castellacci, F. (2021). Digital skills, relatedness and green diversification: A study of European regions. *Research Policy*, 50(9), 104340.

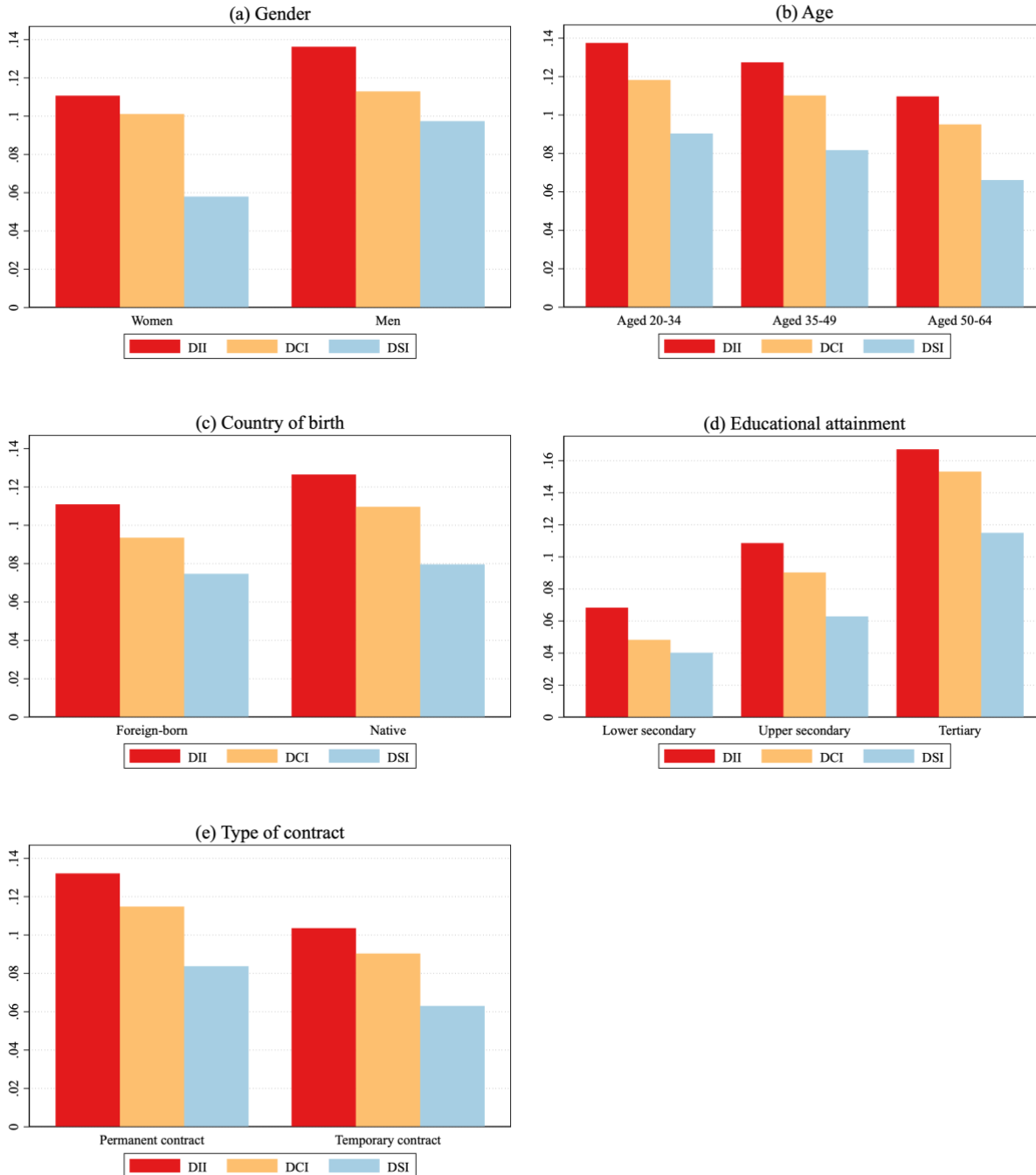
Vuorikari, R., Kluzer, S. and Punie, Y. (2022) DigComp 2.2: The Digital Competence Framework for Citizens - With new examples of knowledge, skills and attitudes, Publications Office of the European Union, Luxembourg, ISBN 978-92-76-48882-8, doi:10.2760/115376, JRC128415.

Webb, M. (2020). The impact of artificial intelligence on the labor market , Available at SSRN 3482150.

Xiao, J., & Boschma, R. (2023). The emergence of Artificial Intelligence in European regions: the role of a local ICT base. *The Annals of Regional Science*, 71(3), 747-773.

Annex

Figure A1. Average digital intensity of work across socio-demographic groups in the EU, 2022



Note: Occupational data at ISCO 3-digit level not available in the EU-LFS for the following Member States: Bulgaria, Malta and Slovenia

Source: Author's elaboration based on indicator values reported in research and the EU-LFS 2022

