Demand for VET skills report: Insights from Online Job Advertisements on Key Occupations in the Green and Digital Transitions

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ABSTRACT

This study investigates how regional characteristics relate to intra-occupational variations in online job advertisements (OJA) for two occupations. It analyses variations in the demand for skills, i.e., the number of occupation-specific and transversal skills, relative importance of those skills, work experience, and the specificity of qualification requirements in relation to the regional context. We focus on two occupations impacted by recent labour market changes: warehouse logistics operators, where formal qualifications act as a relatively weak gatekeeper, and ventilation technicians, where access is more closely tied to a specific vocational qualification. Using natural language processing techniques to extract and classify information from OJA texts, the study finds that requirements differ across regions. For warehouse logistics operators, we observe a small urban specialisation effect, with more occupation-specific skills and more specific formal qualifications required in urban regions. In contrast, ventilation technicians exhibit minimal regional variation in requirements, with weaker regions relying more on recruitment agencies. Overall, the findings suggest that regional labour market conditions influence employer requirements mainly in low-standardised occupations, while in highly standardised occupations, the differences are primarily linked to recruitment practices rather than job content.

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Skills2Capabilities, a Horizon Europe study, is about understanding how skills systems need to develop if they are to assist people to make labour market transitions – i.e. between jobs, employers or sectors – and thereby reduce the level of skill mismatch which might otherwise arise.

This Working Paper is part of the Skills2Capabilitiy Work Package 4 entitled 'Challenges and changes in the demand for VET Skills'

For more information please visit skills2capabilities.eu

Introduction

When firms hire for the same occupation, they not only vary in how effectively they fill these roles but also in their expectations of potential employees. Different factors influence variations within the same occupation, including regional labour market conditions, economic strength, and firm characteristics. Previous research has identified an urban specialisation effect, suggesting that jobs in urban areas generally require more specialised skills than those in rural areas (Kok, 2014; Rouwendal & Koster, 2025). Firms in regions experiencing labour shortages often adjust their recruitment strategies to expand their applicant pool (Brenzel & Müller, 2015). This study builds on previous research by incorporating additional regional factors, such as indicators of structural strength and regional transformation, to enhance the understanding of how these regional characteristics relate to the requirements detailed in online job advertisements (OJAs). It considers not only skill requirements (occupation-specific and transversal) but also formal qualifications to examine which dimensions are more affected by intra-occupational differences.

To examine these relationships, all OJAs web-scraped from Textkernel in 2024 (Textkernel, 2024) who recruited warehouse logistics operators and ventilation technicians were analysed. These two occupations, studied as well in Work Package 2 in the context of curricula updates, exemplify contrasting degrees of standardisation. While formal qualifications for ventilation technicians serve as a significant barrier to employment, they play a relatively minor role for warehouse logistics operators. These two occupations were chosen because they are widely distributed across Germany, provide sufficient data for analysis, differ in labour market demand, and are both relevant to ongoing transformation processes. Ventilation technicians play a key role in the green transition, and warehouse logistics operators are central to the digital transformation of supply chains.

Using Natural Language Processing (NLP), we extracted skill requirements. We mapped them to the German BERUFENET for occupation-specific skills and to the European Competencies and Occupations (ESCO) taxonomy for transversal skills. We extracted formal qualification requirements and, based on them, modelled a potential applicant pool, accounting for the specificity of the required qualifications. Both skill and formal qualification requirements were then linked with regional indicators such as urbanisation, labour market tightness, and structural strength.

Germany serves as a good example for this type of analysis due to its significant regional diversity (Jung et al., 2023) and a well-defined middle segment in the labour market, which is influenced by its highly developed vocational education and training (VET) system. Additionally, the varying levels of standardisation across formal qualifications allow us to investigate whether the hiring strategies differ between firms in different regions based on skills and qualifications.

The following research questions will be addressed.

Research Question 1: Do highly standardised occupations like ventilation technicians differ from low-standardised ones like warehouse logistics operators in their intra-occupational variation in OJA-based skill and qualification requirements?

Research Question 2: To what extent do regional factors shape intra-occupational variation in skill and qualification requirements?

Research Question 3: Does recruitment agencies' engagement vary across regions?

Theoretical Background

Skills and Qualifications

In the context of OJAs, the boundary between skills and tasks is often blurred, as skills can be both explicitly stated and implied by the tasks themselves. In this study, skills are defined as the ability to perform a specific task (Rodrigues et al., 2021). Although the literature discusses numerous types of skills, such as technical, soft, cognitive, or employability skills (Nägele & Stalder, 2017), this study distinguishes only between specific skills (occupation-related) and transversal skills, which are relevant across occupations. This distinction follows Becker's (1964) Human Capital Theory, in which the specificity of skills determines their transferability between jobs.

In qualification-based labour markets such as Germany, formal qualifications play a central signalling role in recruitment. According to Spence's (1973) Job Market Signalling Theory, formal qualifications signal productivity to employers. In Germany, this signalling function is reinforced by a high degree of VET standardisation, driven by uniform curricula aligned with federal or national regulations. These standardised certificates thus serve as strong proxies for bundles of skills and reduce transaction costs in job matching (Dengler et al., 2016; Williamson, 1981). Accordingly, German OJAs list significantly fewer explicit skills than those in the U.S. and other less standardised labour markets, as these are considered implicit in the formal qualifications (Bertelsmann Stiftung & Burning Glass Technologies, 2020). Additionally, evidence from the UK shows a growing shift towards skill-based hiring to expand the pool of potential applicants. This trend is driven by a mismatch between the pace of change in formal education and labour market needs, as well as increasing labour market tightness (Bone et al., 2023).

Some occupations are additionally subject to occupational licensing, which are formal legal provisions that restrict access to or use of a professional title (Vicari & Unger, 2020). If standardisation and licensing are considered together, occupations differ in how strongly access depends on formal qualifications (Vicari, 2014). Vicari's *degree of standardised certification* ranges from 0 (no formal access restriction) to 1 (fully standardised and regulated Accordingly, warehouse logistics operators (0.40) represent a less standardised occupation, where greater intra-occupational variation in formal qualification requirements is possible and, due to the lower importance of formal credentials, skill-based hiring may play a more prominent role. In contrast, ventilation technicians (0.90) are highly standardised, with formal qualifications serving as a strong gatekeeper.

Hypothesis 1: There will be fewer intra-occupational differences in qualifications among ventilation technicians than among warehouse logistics operators.

Regional Determinants of Demand

Regional labour market conditions shape the skills firms require from potential employees. One factor contributing to differences within occupations is the urban environment. The more urban the location, the more skills companies tend to demand in OJA (Garasto et al., 2021; Rouwendal & Koster, 2025). This observation aligns with the central place theory proposed by Christaller (1933), which states that occupations in larger agglomerations tend to become more specialised, while those in smaller or lower-order settlements remain more generalist. The urban specialisation effect is mainly found among craft, professional, and service occupations, particularly among medium- and high-skilled workers (Garasto et al., 2021; Kok, 2014). This effect persists even when controlling for firm size (Rouwendal & Koster, 2025), another context in which more specialised workers are required as firm size increases (Adenbaum, 2023; De Vera & Garcia-Brazales, 2021). Larger firms also tend to require more work experience and stronger cognitive and social skills than smaller firms (Deming & Kahn, 2017).

However, analysing urban–rural differences without considering other regional characteristics risks oversimplification. Structural and demographic factors, such as ageing, unemployment, wage levels, and the occupational and firm-size composition, influence, for example, the severity of recruitment difficulties (Buch et al., 2024). Labour market tightness is a second major factor shaping intra-occupational variation.

The IAB Establishment Panel shows that 64% of German firms reported difficulties in recruiting skilled workers in 2024 (Hohendanner et al., 2025), which affects recruitment processes in multiple ways, as employers are often compelled to adapt their recruitment strategies to expand the applicant pool. For example, firms facing hiring difficulties increasingly target new applicant groups, such as refugees or recruit workers from abroad, and make working hours more flexible to attract parents or part-time employees (Stippler et al., 2019; Weis, 2019). According to Reder's (1955) hypothesis, employers may respond to a shortage of qualified candidates by either lowering hiring standards to enlarge the applicant pool or raising wages. Empirical research confirms that companies do adjust requirements in response to staffing problems. Brenzel and Müller (2015) show that, in response to staffing problems, 12% of companies lower qualification or experience requirements, 10% raise wages, and 2% do both. Moreover, hiring costs increase disproportionately in tight labour markets, incentivising firms to accept less-than-ideal candidates and invest more in post-hiring training. Recent empirical evidence supports this: firms in tight labour markets systematically lower their hiring standards for applicants' general abilities (Linckh et al., 2024). It remains unclear whether firms in regions with hiring difficulties also have different requirements for their OJA. Causal conclusions about whether firms actively lower their standards in response to labour shortages would require longitudinal data. However, it can reasonably be assumed that firms in regions facing recruitment problems are more flexible towards career changers and tend to formulate lower qualification requirements.

The relationship between additional regional factors, such as structural transformation and regional attractiveness, and job requirements in OJA has not yet been explored. Regional attractiveness reflects the perceived quality of life and economic prospects of a region. Structural transformation (as visualised in Deliverable WP4.1) in Germany usually refers to the former coal mining areas and the former East Germany. This transformation, for example, in Lusatia, Germany, is accompanied by demographic shifts, including an aging population, net outmigration exceeding in-migration, declining population levels, and a decrease in municipal revenues (Lebhart & Noack, 2025). Particularly, regions like that are facing significant skill mismatches as their industrial focus shifts away from carbon-intensive sectors. These regions are characterised by the outmigration of qualified workers and the loss of entire occupational fields, leading to a shortage of candidates with the necessary skills for emerging industries (Radtke & David, 2024). Facing a shrinking labour pool and an increasing skill mismatch, companies may adopt more flexible, skill-based hiring practices to complement public requalification efforts.

Hypothesis 2a: In more urban regions, employers demand a higher number of occupation-specific skills and more specific formal qualifications, reflecting higher job complexity.

Hypothesis 2b: In regions with high labour market tightness, employers formulate broader qualification requirements, fewer occupation-specific requirements, and more transversal skills to enlarge the pool of applicants.

Hypothesis 3a: The share of OJA placed by recruitment agencies is higher in structurally weak, unattractive, or transforming regions.

Hypothesis 3b: The regional use of recruitment agencies is more pronounced in highly standardised occupations (e.g., ventilation technicians) than in less standardised ones (e.g., warehouse logistics operators).

The Case of Germany

Germany continues to show significant structural disparities among its regions. Following reunification, the eastern districts faced unemployment rates twice as high and wages approximately 30% lower than in the West. Although the gap has narrowed over time, considerable differences still exist. For example, southern regions such as Bavaria and Baden-Württemberg demonstrate high productivity, elevated wages, and low unemployment rates, whereas several western districts, particularly in North Rhine-Westphalia, continue to lag (Jung et al., 2023). In theory, increased spatial mobility could help address these imbalances by enhancing labour market matching. However, mobility among workers with vocational qualifications remains relatively low, especially when compared to that of university graduates (Ganesch et al., 2019). This situation reinforces regional labour-market segmentation.

This paper focuses on two occupations that illustrate how regional conditions shape skill demand in the green sector (ventilation technicians) and the digital transformation sector (warehouse logistics operators).

Ventilation technicians install and maintain water, heating, and air-conditioning systems. Their tasks include connecting sanitary facilities, integrating renewable systems such as solar panels or heat pumps, testing system functionality, configuring smart-home controls, and advising customers on energy efficiency (Bundesagentur für Arbeit, 2025a). They are key actors in the green transition, as their work directly contributes to the development of energy-efficient buildings. In Germany, work on drinking water and gas installations is legally restricted to qualified professionals

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under the *Handwerksordnung* (HwO, Annexe A No. 24), the *Technical Rules for Gas Installations* (DVGW G 600, 2018), and the *Technical Rules for Drinking Water Installations* (DVGW W 551, DIN EN 806-4). Manufacturers typically only guarantee their products when installed by licensed professionals. If unqualified helpers do the work, the warranty and liability become invalid. That is why formal qualification plays such an important role in this occupation. Approximately 140,000 people are employed in this occupation, with an average vacancy duration of 106 days (Bundesagentur für Arbeit, 2024a).

Warehouse logistics operators receive, inspect, store, and dispatch goods. They plan and document internal material flows, operate forklifts and other transportation equipment, and prepare shipping documentation. Beyond physical handling, they increasingly manage digitalised supply-chain processes and contribute to structural and digital transformation in logistics (Bundesagentur für Arbeit, 2025b). Approximately 610,000 people are employed in this occupation, with an average vacancy duration of 64 days (Bundesagentur für Arbeit, 2024b). Occupations in transport, warehousing, and logistics (KldB-1-digit), along with cleaning and waste disposal occupations, have the highest employment of individuals without formal qualifications (Maier et al., 2015).

These two occupations illustrate two complementary aspects of Germany's transformation: the green transition in building technology and the digital transition in logistics. Both sectors are prevalent nationwide, but they differ in labour market tightness, the degree of standardisation, and the potential for regional variations in hiring practices.

Data and Methods

Data and filtering

The research questions are addressed using commercially acquired OJA web-scraped between January 2024 and December 2024 (Textkernel, 2024), including OJA published by the German Federal Employment Agency. TextKernel ensured deduplication and provided ISCO coding in the metadata. From the full 2024 dataset, only those coded as ISCO 7126 (ventilation technician) or ISCO 4321 (warehouse logistics operators) were retained. To refine the sample, several exclusion criteria were applied: OJA in languages other than German, OJA for apprenticeship positions, roles explicitly requiring a university degree (ISCED 5 or higher), and all OJA lacking workplace coordinates. After the skill assignment process, all OJAs that did not contain any occupation-specific skills, as well as those published by recruitment agencies, were excluded from the regional analyses. Approximately 380,000 OJAs were analysed in total. Of these, 65,802 OJAs were for ventilation technicians (26,093 posted by recruitment agencies), and 312,277 were for warehouse logistics operators (177,008 posted by recruitment agencies). OJAs posted by recruitment agencies were excluded from the regional analyses.

Recruitment agencies published a large proportion of OJAs. These are identified based on keywords. However, these OJAs are not included in the regional analyses because only the location of the recruitment agency is available in the metadata, not the actual workplace location, and the actual firm is usually not revealed in the text. Additionally, it is common for the same recruitment agency to be used for hiring across multiple regions. This could introduce bias into regional comparisons if these cases were included. Another issue is that it is not clear whether there is actually a vacancy to fill, because recruitment agencies may advertise positions to build a candidate pool that can be utilised for direct placement as soon as a job order is received.

Preprocessing of OJAs' information extraction

Several preprocessing steps were performed in Python to retrieve the requirements from the OJAs. The complete preprocessing code is available in the supplementary material (here).

1. Noise reduction: URLs, addresses, boilerplate phrases like "We look forward to receiving your application", contact details, and advertisements for similar job offers found within OJAs were eliminated using the *re* library for regular expressions (Van Rossum, 2020).
2. Whitespace and character normalisation: Whitespace was normalised to ensure consistent formatting throughout the texts. Additionally, standard abbreviations were expanded to their complete forms (e.g., “inkl.” to “inklusive,” “usw.” to “und so weiter”) to facilitate sentence segmentation, as punctuation would separate these sentences.
3. Sentence segmentation: The whole text was then segmented into individual sentences using the Natural Language Toolkit (nltk) for Python (Bird et al., 2009). A sentence in this context ends with a punctuation mark or is a bullet point in a list.

After completing the preprocessing steps, the information extraction process began. In total, 1,220 sentences were manually labelled using Label Studio (Tkachenko et al., 2020) for a coarse-grained extraction of skills and qualifications. Each sentence was labelled as either "relevant" or "none". To address class imbalance, the synthetic minority over-sampling technique (SMOTE; Chawla et al., 2002) was utilised to balance the dataset by oversampling the minority class. Furthermore, data augmentation techniques, including synonym replacement and random deletion, were employed. These methods expanded the dataset and introduced variability, thereby making the model more robust to language variation (Wei & Zou, 2019).

Subsequently, JobBERT-de (Gnehm et al., 2022), a transformer-based model, was fine-tuned using this manually annotated dataset. JobBERT-de is a domain-specific BERT model, pre-trained on Swiss German OJAs, making it well-suited for understanding context-specific language in the field of OJA. The fine-tuning focused on distinguishing sentences that mention qualifications or skills from those that do not. As a result, further analyses were performed on a much smaller dataset, reducing the risk of incorrectly identifying skills or formal qualifications in sentences not relevant to the research question. For instance, the company's characteristics will not be mistaken for those of the potential employee, and other job openings advertised within an OJA will not be misinterpreted as qualifications for the potential employee. The fine-tuned model then predicted, for each sentence of each OJA, whether the sentence contained requirements for applicants.

Fine-tuning of JobBERT-de

To fine-tune JobBERT-de to distinguish between sentences that mention qualifications or skills and those that are irrelevant, the annotated dataset was split into training (80%), validation (10%), and test (10%) sets. The model was trained on the training set for three epochs with a batch size of 8, resulting in a total of 109,084,420 trainable parameters. During training, the model showed performance improvements, with an initial loss of 0.8184 decreasing to a final training loss of 0.1797. The final model was evaluated on the test set and achieved 97.54% accuracy, 97.65% precision, 97.54% recall, and 97.54% F1-score. The Python code and the fine-tuned model are available for download here.

Skill assignment

A two-step pipeline was used to assign the requirement sentences to skill categories. Separate dictionaries were created for occupation-specific skills and transversal skills. For occupation-specific skills, a BERUFENET-based dictionary was compiled for each occupation, which included example sentences for all listed skills. For transversal skills, an ESCO-based dictionary was developed, organised into cognitive, social, physical, and self-management dimensions. These two dictionaries were merged to build the classification training data, complemented by additional categories such as formal qualification, work experience, and a residual category for skills not related to any of the predefined categories.

Each skill category contains, on average, 20 OJA-derived training sentences. First, a string lookup was done to match the OJA sentences with the training sentences. Second, a multi-label classifier was employed to predict skills beyond explicit string matching. Each dictionary sentence was encoded using the Hugging Face Transformer model bert-base-german-case (Chan et al., 2019), with padding and truncation, and a mean-pooled vector over the last hidden states was computed. Embeddings were z-standardised before classification. For each category, a one-vs-rest logistic regression with 20,000 maximal iterations was trained. In this setup, a binary classifier was trained for each skill category, meaning that each sentence from the OJAs was independently evaluated against each category, enabling multi-label assignment. A probability threshold of 0.45 was used for assignment. To counter class imbalance, SMOTE oversampling was combined with random undersampling of negative classes. Hard negative sampling was introduced to improve classification boundaries by selecting negative samples that are semantically similar to positive ones but do not belong to the target category. The top 10% most similar negative examples were selected as hard negatives based on cosine similarity, in line with the approach described by Clavié and Soulié (2023). By training the model to make fine-grained distinctions between closely related skills, hard negatives help reduce misclassification errors and enhance generalisation (Robinson et al., 2021). Model selection and reporting used Stratified K-Fold CV with 10 splits. The classification quality, as measured by F1 score, recall, and precision, is presented in Appendix A and B. This process was iterative: misclassified examples were systematically reviewed, and similar instances were added to the training data to improve the model's performance.

Specificity indicators

The first section explains how the qualifications mentioned in OJAs are used to model the potential applicant pool size. The second section illustrates how the skill specificity and skill profiles were measured. To assess the specificity of qualifications, all sentences classified under the labels "Job Title," "Formal Qualification," or "Work Experience" were considered. For the skill specificity, all sentences labelled as occupation-specific and transversal skills were considered.

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Skill coverage indicator

The skill coverage indicator reflects the proportion of mentioned skills in the OJA relative to the BERUFENET core competencies from the corresponding vocational training. All sentences from the OJA that were labelled as relevant by the fine-tuned JobBERT-de (Gnehm et al., 2022) model were embedded using the standard BERT model bert-base-german-cased (Chan et al., 2019).

SMOTE was applied to enhance the representation of minority classes. The SMOTE-enhanced training sets were fed into logistic regression classifiers, which were cross-validated using stratified K-Fold cross-validation with 10 splits (Kohavi, 1995), ensuring balanced training across categories.

Specificity of formal qualification

The pool size refers to the potential size of the applicant pool, based on the qualifications required in OJA. It is intended to reflect how narrowly or broadly the requirements for a given position are defined. Particular interest lies in cases where employers accept different qualification levels (vertical flexibility) or alternative vocational degrees (horizontal flexibility). To systematically operationalise pool size, an ordinal scoring model was developed to weight different qualification requirements. Formal qualifications and work experience requirements were classified into binary categories depending on the occupation:

Ventilation technician: No formal qualification required and no work experience (largest pool); No formal qualification but work experience required; Either vocational training or work experience is accepted; Vocational training described with an umbrella term such as “technical training”; Vocational training described with an umbrella term such as “technical training” and work experience; Ventilation technician; Ventilation technician plus work experience (smallest pool).

Warehouse logistics operator: No formal qualification required and no work experience (largest pool); No formal qualification but work experience required; Either vocational training or work experience is accepted; Acceptance of a vocational degree outside logistics or an umbrella term such as “commercial training”; Fachlagerist (two-year vocational training); Fachkraft für Lagerlogistik (three-year vocational training; smallest pool).

All sentences labelled as formal qualification, job title, or work experience were considered. Then, a training dataset was created by labelling all sentences as a whole to maintain semantic coherence. For instance, if qualifications and work experience were classified independently, cases where work experience is considered equivalent to formal qualifications as a requirement might be overlooked.

A machine learning model was applied to classify text-based qualification requirements into these categories. The dataset consisted of 275 training examples and 70 test examples. The model was trained using a TF-IDF vectorizer and a OneVsRest logistic regression classifier with class balancing.

Regional skill importance

To measure the regional importance of individual skills, a procedure similar to Fabo et al. (2017) was applied. Central to this process is the calculation of a Skill Importance Index (SII), which measures the frequency with which a specific skill is explicitly required in OJA for a given region and occupation. For region *r*, occupation *b*, and skill *s*, the Skill-Importance Index is defined as:

$$SII_{r,o,s}\frac{Number\ of\ OJA\ in\ region\ r\ for\ occupation\ o\ requiring\ skill\ s}{Total\ number\ of\ OJA\ in\ region\ r\ for\ occupation\ o}$$

The index thus provides a relative frequency measure in the range [0,1], representing the share of OJA in which a skill is required.

Regional/spatial indicators

To establish the specificity of job requirements in relation to regional factors, a series of indicators was selected to operationalise the overarching concepts. These regional indicators are considered at the most minor possible spatial units (NUTS-3 or employment agency districts). They are sourced from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR), 2025) and KOFA (2025) for data on occupation-specific labour-market tightness, and the Equivalence Report of the Federal Government (Gleichwertigkeitsbericht, Bundesministerium für Wirtschaft und Klimaschutz (BMWK), 2024) for subjective measures. Data are drawn from the most recent year.

For **economic strength**, the selected indicators include GDP per capita, income tax revenue, median income, capital expenditure, and the unemployment rate.

For **urbanisation**, the indicators are rurality and perceived quality of public transport.

Attractiveness is operationalised through the availability of recreational areas, the number of overnight stays (as a proxy for tourism), subjective life satisfaction, satisfaction with career prospects, and land prices for building.

The **availability of employees** is modelled using occupation-specific indicators at the 3-digit level of the KldB, including the number of open positions, the number of unemployed individuals at the specialist level, employment in the secondary sector, the number of open positions requiring specialist skills, the number of employees in the crafts sector, and the proportion of employees with a vocational qualification.

Transforming regions are characterised by the receipt of urban development funding (both short-term and long-term), financial support from the Structural Transformation Fund (GRW), the average age of the population, commuter balances, early-career migration, and net migration.

Analyses

To test the hypotheses, we correlate the previously mentioned regional indicators to multiple operationalisations of skills, qualifications, and employers' use of recruitment agencies as a recruitment channel. First, we assess whether the number of required skills can serve as a proxy for job complexity by correlating both transversal and occupation-specific skill counts with the specificity of qualifications and work experience requirements. Second, we examine whether regional conditions are associated with intra-occupational variation by linking the number of skills and the specificity of formal qualifications to regional indicators. Third, we analyse the regional distribution of recruitment agency postings to identify occupational differences in recruiting practices among employers. Finally, we inspect regional skill profiles using the Skill Importance Index to determine whether certain skills are more prominent in some regions than others. In summary, these analytical steps provide the empirical strategy for evaluating Hypotheses 1–3 and for identifying the extent to which regional patterns emerge.

Number of skills = Complexity of job?

Tables 1 and 2 present the correlation between skill and qualification variables by occupation. In both occupations, more specific qualifications are required as occupation-specific skills increase. In addition, more transversal skills are required as occupation-specific skills increase. The full sample, including OJA from recruitment agencies, was taken into account for these analyses.

Table 1

Ventilation technicians: Correlations between required skills, working experience and pool size

Variable 1	Variable 2	*r*	*p*	*N*
FQ specificity	Occupation-specific skills	.16	< .001	65,193
Work experience (pb)	Occupation-specific skills	-.03	< .001	65,311
FQ specificity	Transversal skills	-.08	< .001	65,193
Work experience (pb)	Transversal skills	.08	< .001	65,311
Transversal Skills	Occupation-specific skills	.24	<.001	65,311

Note. *r* = Pearson correlation coefficient, pb = point-biserial correlation. Work experience is a binary variable; FQ specificity refers to the specificity of formal qualifications.

Table 2

Warehouse logistics operator: Correlations between required skills, working experience and pool size

Variable 1	Variable 2	*r*	*p*	*N*
FQ specificity	Occupation-specific skills	.29	< .001	312,277
Work experience (pb)	Occupation-specific skills	.13	< .001	281,644
FQ specificity	Transversal skills	-.02	.903	312,277
Work experience (pb)	Transversal skills	.09	< .001	281,644
Transversal Skills	Occupation-specific skills	.22	<.001	312,277

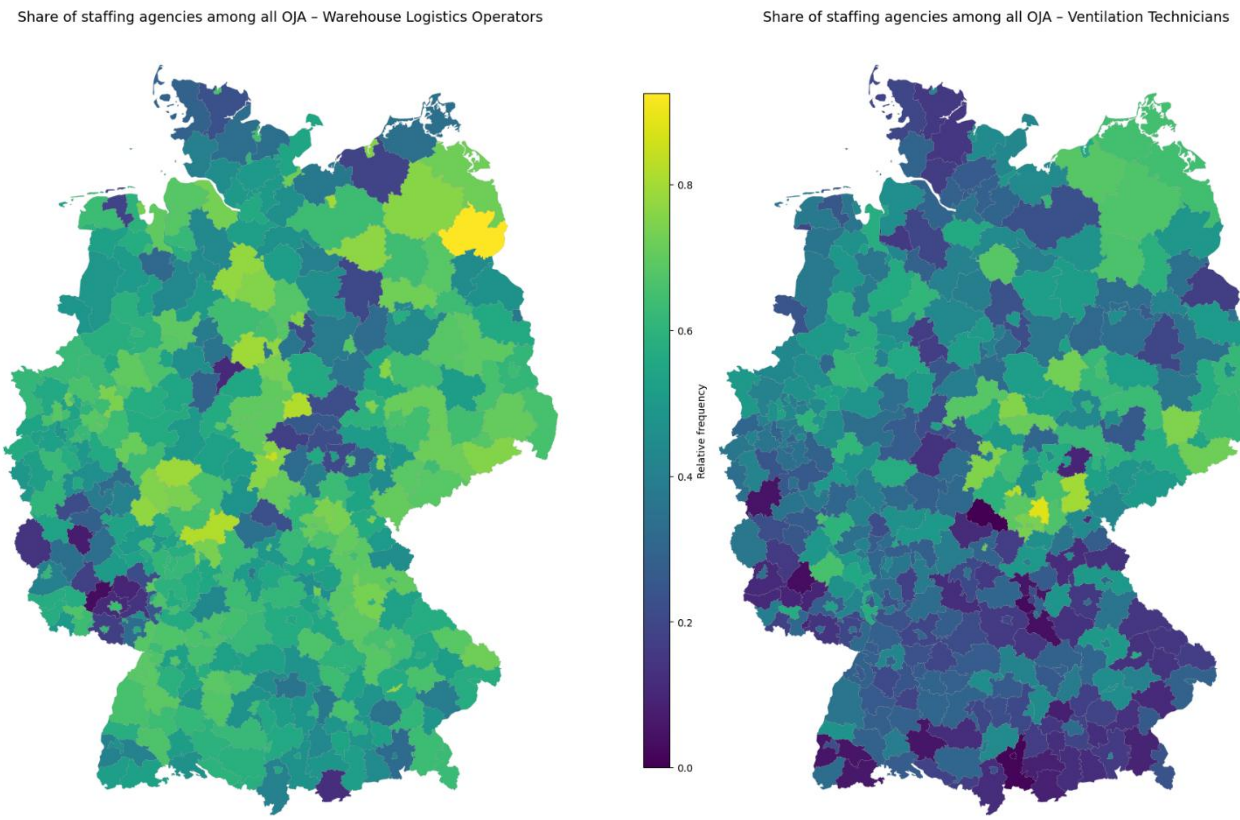
Note. *r* = Pearson correlation coefficient, pb = point-biserial correlation. Work experience is a binary variable; FQ specificity refers to the specificity of formal qualifications.

Share of OJA from recruitment agencies

Across all NUTS-3 regions, Figure 1 shows that warehouse logistics operators have a higher share of OJA posted by recruitment agencies compared to ventilation technicians. Moreover, the share for warehouse logistics operators appears to be more evenly distributed across Germany. In contrast, for ventilation technicians, higher shares are concentrated in the eastern regions, particularly in Saxony-Anhalt and Mecklenburg-Western Pomerania.

Figure 1

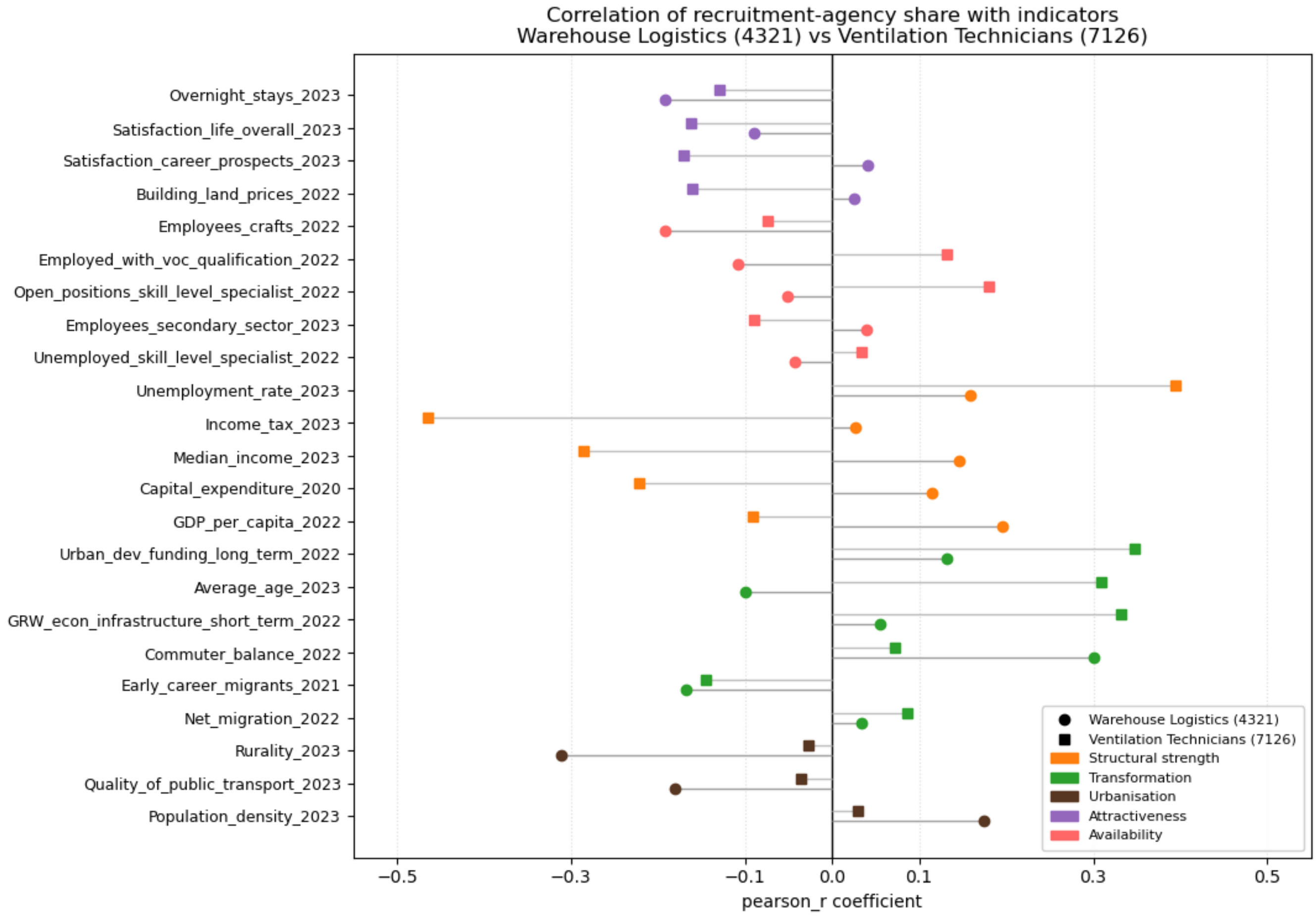
Share of OJA published by recruitment agencies of all OJAs, depending on occupation



The underlying regional factors associated with these differences are illustrated in Figure 2 through correlations with structural characteristics. The figure indicates that the use of recruitment agencies varies by region for the two occupations. For warehouse logistics operators, correlations with regional indicators are minor and scattered, suggesting no clear regional pattern. For ventilation technicians, the agency share is strongly linked to regional conditions: it is higher in structurally weak and transforming regions (e.g., higher unemployment, GRW funding) and lower in economically stronger and more attractive regions (e.g., higher incomes, greater life satisfaction).

Figure 2

Correlations between recruitment agency share and regional indicators for warehouse logistics and ventilation technicians



Regional patterns of skill requirements and the specificity of formal qualification

Figures 3 and 4 depict the relationships among occupation-specific skills, transversal skills, and the specificity of formal qualifications for ventilation technicians and warehouse logistics operators, in relation to regional indicators. Overall, regional indicators show weak correlations with OJA requirements. For ventilation technicians, correlations are consistently minimal and close to zero across all indicators. In contrast, warehouse logistics operators exhibit small positive correlations with occupation-specific skills and qualification specificity, particularly with urbanisation and structural strength, suggesting slightly more complex or specific requirements in stronger, urbanised regions. However, transversal skills display little to no regional pattern for either occupation.

Figure 3

Ventilation technicians: Correlations of regional indicators with OJA requirements

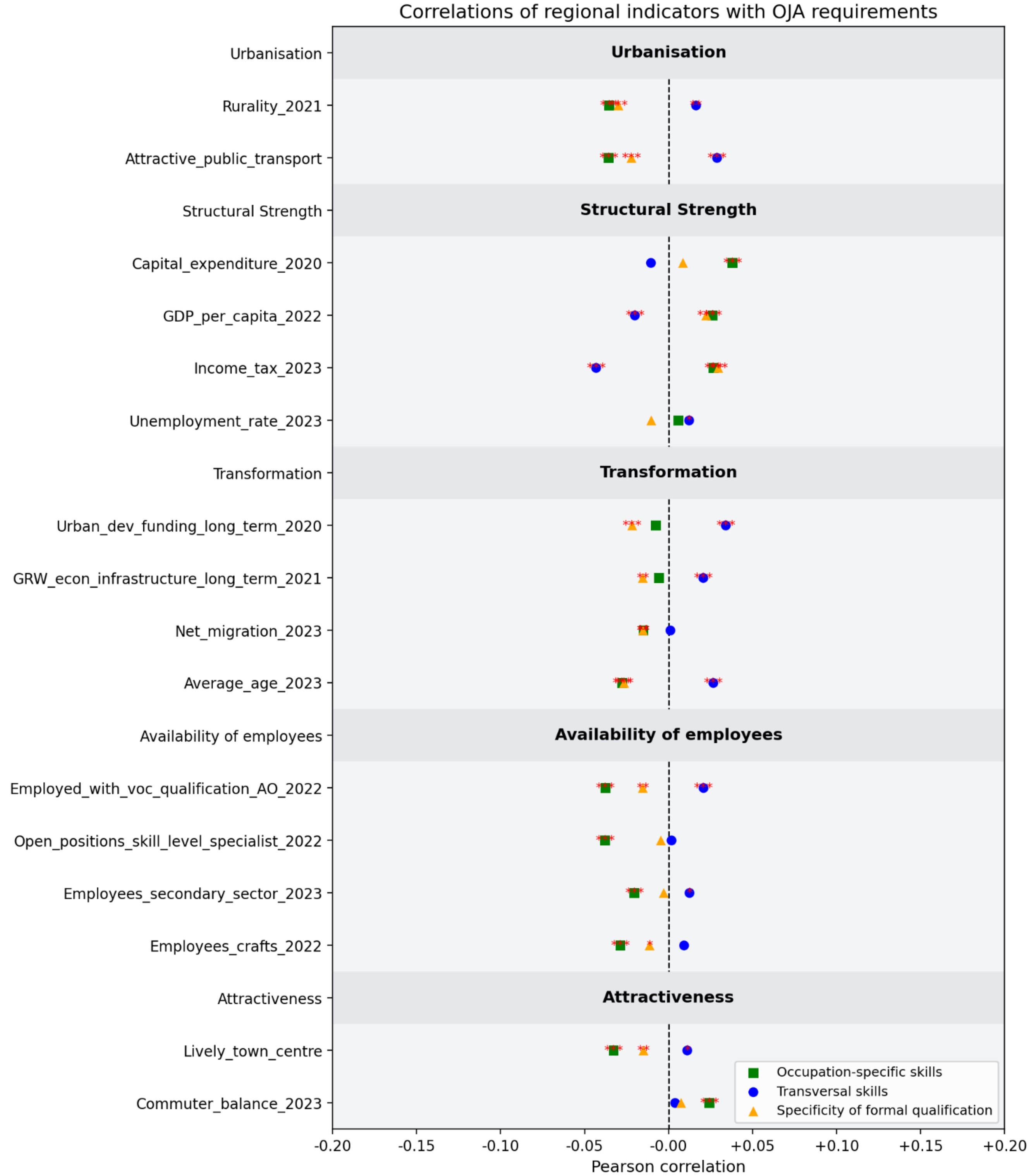


Figure 4

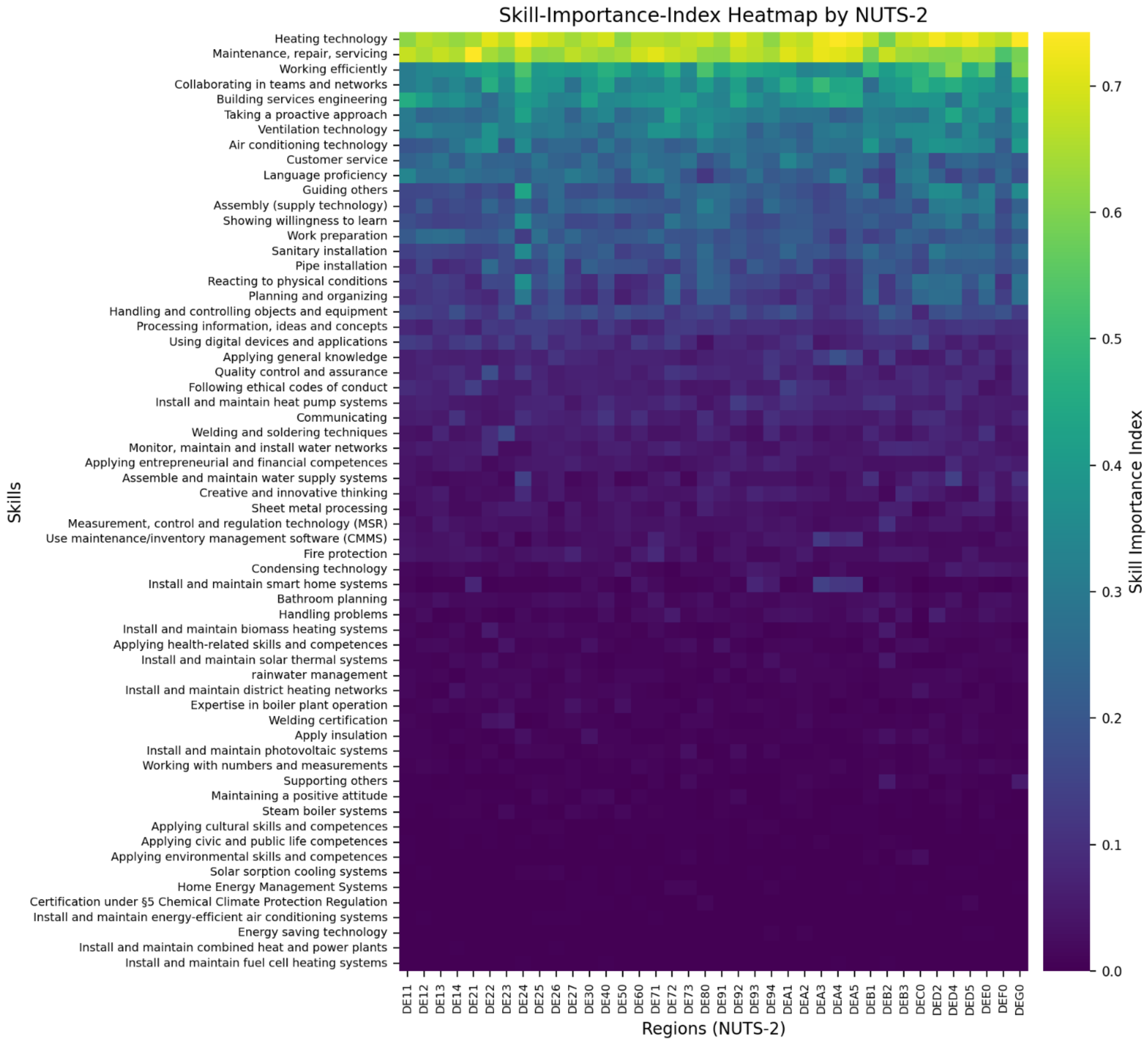
Warehouse logistics operators: Correlations of regional indicators with OJA requirements

Skill Importance Index

The Skill Importance Index visualises the skill profiles for each region. The lighter/more yellow the pixel for each NUTS region, the more frequently the skill is mentioned in that region relative to all other skills. The more similar the colours in each row, the smaller the regional differences, as shown in Figures 5 and 6. This indicates that regional variation in the explicit demand for individual skills is limited and does not reflect distinct regional skill compositions; rather, differences arise from small variations in the overall number or specificity of required skills.

Figure 5

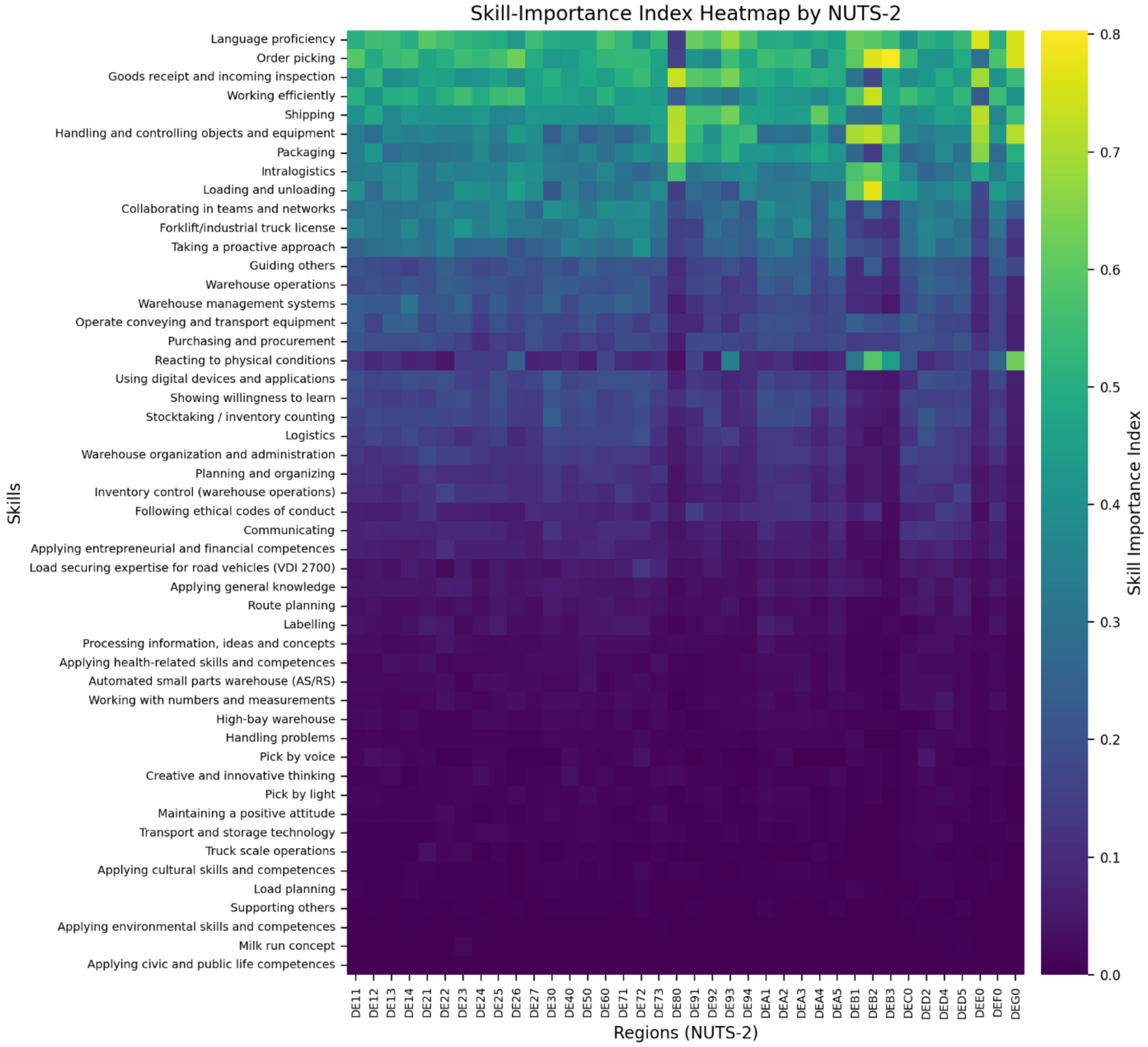
Ventilation technicians: Skill Importance Index by NUTS-2 region



Note. Values reflect the relative frequency of skill mentions in OJAs. The index ranges from 0 = never mentioned to 1 = mentioned in all OJAs for that region. Skills are ordered by decreasing importance.

Figure 6

Warehouse logistics operator: Skill Importance Index by NUTS-2 region



Note. Values reflect the relative frequency of skill mentions in OJAs. The index ranges from 0 = never mentioned to 1 = mentioned in all OJAs for that region. Skills are ordered by decreasing importance.

Discussion

The results suggest differences between the two occupations in how regional factors are related to OJA requirements and recruitment strategies.

The relative importance of individual skills (Skill-Importance Heatmap) shows slight regional variation for ventilation technicians, as indicated by the minimal colour differences across regions. For warehouse logistics operators, there is slightly more variation, but not to an extent that would suggest a clear relationship with regional factors.

The number of occupation-specific skills was used as an indicator of job complexity and specialisation, consistent with prior research (Chaturvedi et al., 2023; Garasto et al., 2021; Rouwendal & Koster, 2025). The specificity of formal qualifications is positively correlated with occupation-specific skills in both occupations. For warehouse logistics operators, the correlation coefficient is .29, while for ventilation technicians, it is .16. This aligns with previous findings that indicate a greater number of skills listed in OJAs is generally associated with higher qualification levels (CEDEFOP, 2019). However, the more negligible effect observed for ventilation technicians may indicate that the difference in the mentioned skills between unskilled workers and qualified professionals is relatively small. This could be due to the strong signalling value of formal qualifications in this occupation, which reduces the need for employers to list additional specific skills. In contrast, for unskilled positions, a more detailed task description is necessary to communicate expectations clearly.

Regarding **Hypothesis 1**, the findings confirm that highly standardised occupations show less intra-occupational variation in terms of qualifications. Ventilation technicians, a highly standardised and licensed occupation, display almost uniform OJA requirements across regions, with only minor correlations (all below .10) between regional indicators and both skill and formal qualification requirements. The highest correlations are observed for transversal skills, suggesting minimal scope for employers to adjust qualification or occupation-specific skill requirements. The data for ventilation technicians do not permit further interpretations of regional factors. In contrast, warehouse logistics operators, as a low-standardised occupation, exhibit greater variation in skill and qualification requirements, reflecting greater flexibility in how employers define requirements within the same occupation. For warehouse logistics operators, addressing **Research Question 2** reveals a small urban specialisation effect: firms in urban and economically stronger regions tend to list more occupation-specific skills and more specific formal qualifications. This provides support for **Hypothesis 2a**, which expected higher job complexity and more specific qualification demands in more urban regions, in line with previous research (Kok, 2014; Rouwendal & Koster, 2025).

Regarding **Hypothesis 2b**, the data provide no evidence that firms in regions with labour shortages require fewer skills or less specific qualifications than those in other regions. Several explanations are plausible. First, employers may initially maintain formal requirements in job advertisements but make concessions later in the recruitment process. First, employers may initially maintain formal requirements in job advertisements but make concessions later in the recruitment process. Thus, if less-qualified candidates are eventually hired and post-matching costs are higher (Blatter et al., 2012; Linckh et al., 2024), this is likely not because firms initially demand less, but because they are unable to attract better-qualified applicants. Second, the data on occupation-specific labour market tightness may not be appropriate or granular enough to capture a difference.

To address **Research Question 3**, recruitment agencies play a significant role in hiring warehouse logistics operators across regions. In fact, for this occupation, recruitment agencies publish more OJAs than employers recruiting directly, indicating a standardised, institutionalised hiring channel. The regional pattern is weak: correlations with regional indicators are small and inconsistent. Der Share ist vor allem in städtischen Regionen höher.

For ventilation technicians, a highly standardised and licensed occupation, recruitment agencies also play a role, but the pattern differs. Although the total number of OJAs posted by agencies is less than half of those posted directly by employers, the regional pattern is much stronger. Agency involvement is concentrated in structurally weak and/or transforming regions in East Germany, particularly in Saxony-Anhalt, Thuringia, and parts of Saxony. The share of recruitment agencies for ventilation technicians is negatively associated with GDP per capita, median income, municipal tax revenues, and life or career satisfaction. In contrast, it is positively associated with indicators of structural transformation, such as GRW funding volumes and unemployment rates. This pattern partially supports Hypothesis 3a, which predicted greater engagement by recruitment agencies in structurally weak, unattractive, or transforming regions. This relationship is exclusive to ventilation technicians. This aligns with **Hypothesis 3b**, which expected that regionally structured agency use would primarily occur in highly standardised occupations, while low-standardised occupations show little regional differentiation.

This pattern indicates that the intensity of recruitment agency use in a region is linked to weaker labour market conditions and lower local appeal, particularly in highly standardised occupations. This may be due to the low permeability for entry from outside the occupation. Because employers have limited ability to adjust qualification requirements in these occupations, they may rely more on alternative recruitment channels, such as recruitment agencies.

Regarding transversal skills, both occupations predominantly list conventional competencies such as working efficiently, teamwork, or taking a proactive approach, indicating largely standardised phrasing rather than region-specific requirements.

Limitations

There are substantial differences in the accuracy with which the classifiers assigned skills to their occupation-specific skill category. This can be explained by the semantic overlap between some occupation-specific skills, such as heating technology and installing and maintaining fuel cell heating systems. Such overlap creates ambiguity in text classification.

The OJA dataset may also be subject to several biases. Multi-position advertisements that include several roles in a single posting can distort the representation of skill and qualification requirements. Moreover, access restrictions during web scraping prevented the inclusion of sector-specific job portals that require login credentials, likely resulting in an underrepresentation of specific industries (Bertelsmann Stiftung & Burning Glass Technologies, 2020). Additionally, large companies are often overrepresented, while SMEs and low-skilled workers are underrepresented (Cedefop, 2018). Finally, data on firm size were limited, which constrained the interpretability of results regarding company-level differences. Future research could benefit from richer OJA metadata or from integrating firm-level characteristics to better capture organisational variation in hiring practices.

Outlook

Since little variation was found in the requirements for ventilation technicians, indicating limited scope for employers to adjust skill or qualification demands, but a strong regional effect emerged in the use of recruitment agencies, it is plausible that other region-specific hiring strategies exist that are not captured through OJA requirements. Future research could examine additional aspects of OJAs, particularly the benefits offered to employees. These could include mobility-related benefits, such as company cars or public transport subsidies in rural areas, as well as higher wages to offset regional disadvantages and attract qualified workers. In Germany, salary information is often not included in OJAs. However, this may change with the implementation of the EU Pay Transparency Directive, which must be integrated into national law by June 2026. Once enacted, employers will be required to disclose either the entry-level salary or the salary range in the job posting or before the first interview (Directive (EU) 2023/970, 2023). This transparency could create new dynamics in recruitment practices and more effectively highlight regional salary differences.

Moreover, future studies could analyse the degree of flexibility in requirements expressed in OJAs. In the current approach, the applicant pool was modelled based on qualifications explicitly stated as requirements, whereas softening attributes such as "preferred", "desirable," or "advantageous" were not considered. Accounting for such qualifiers would provide a more nuanced understanding of how strictly employers enforce qualification standards and how this flexibility may vary across regions and occupations.

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Appendix A: Warehouse logistics operator, BERUFENET skills classification report

Category	Precision	Recall	F1 Score
Guiding others	0.71	0.77	*M* = 0.75, *SD* = 0.31
Supporting others	0.20	0.10	*M* = 0.10, *SD* = 0.30
Applying health-related skills and competences	0.64	0.54	*M* = 0.48, *SD* = 0.42
Applying cultural skills and competences	0.70	0.70	*M* = 0.63, *SD* = 0.43
Applying environmental skills and competences	0.92	0.86	*M* = 0.85, *SD* = 0.30
Applying entrepreneurial and financial competences	0.44	0.29	*M* = 0.30, *SD* = 0.38
Applying general knowledge	1	0.67	*M* = 0.60, *SD* = 0.49
Working with numbers and measurements	0.82	0.64	*M* = 0.68, *SD* = 0.38
Using digital devices and applications	0.71	0.71	*M* = 0.69, *SD* = 0.31
Maintaining a positive attitude	0.36	0.29	*M* = 0.30, *SD* = 0.38
Following ethical codes of conduct	0.75	0.70	*M* = 0.37, *SD* = 0.46
Language proficiency	0.84	1	*M* = 0.93, *SD* = 0.12
Working efficiently	0.5	0.39	*M* = 0.40, *SD* = 0.35
Handling and controlling objects and equipment	0.88	0.5	*M* = 0.53, *SD* = 0.45
Handling problems	0.99	0.89	*M* = 0.80, *SD* = 0.40
Communicate	0.5	0.42	*M* = 0.45, *SD* = 0.36
Applying civic and public life competences	0.75	0.64	*M* = 0.69, SD = 0.40
Creative and innovative thinking	0.6	0.33	*M* = 0.27, *SD* = 0.42
Planning and organising	0.6	0.27	*M* = 0.27 *SD* = 0.42
Reacting to physical conditions	0.62	0.57	*M* = 0.55, SD = 0.39
Processing information, ideas and concepts	0.82	0.75	*M* = 0.73 *SD* = 0.39
Taking a proactive approach	0.62	0.53	*M* = 0.48, SD = 0.34
Showing willingness to learn	0.42	0.38	*M* = 0.35, SD = 0.37
Collaborating in teams and networks	0.6	0.30	*M* = 0.27 *SD* = 0.42
Working Conditions	0.99	0.77	*M* = 0.77 *SD* = 0.40
Work experience	0.88	0.83	*M* = 0.81 *SD* = 0.30
Job title	0.86	0.95	*M* = 0.91 *SD* = 0.12
Formal Qualification	0.81	0.94	*M* = 0.88, *SD* = 0.17
Other skills	0.54	0.40	*M* = 0.44, *SD* = 0.22
Certificates and Licences	0.94	0.84	*M* = 0.88, *SD* = 0.18
Automated small parts warehouse	0.99	0.64	*M* = 0.70, *SD* = 0.46
Loading and unloading	0.72	0.57	*M* = 0.69, *SD* = 0.29
Load planning	0.71	0.83	*M* = 0.76, *SD* = 0.31
Inventory control	0.65	0.63	*M* = 0.61, *SD* = 0.27
Purchasing and procurement	0.53	0.42	*M* = 0.43, *SD* = 0.32
Labelling	0.99	0.79	*M* = 0.77, *SD* = 0.40

Operate conveying and transport equipment	0.65	0.70	*M* = 0.68, *SD* = 0.20
Forklift license	0.64	0.60	*M* = 0.49, *SD* = 0.43
High-bay warehouse	0.91	0.91	*M* = 0.87, *SD* = 0.31
Intralogistics	0.45	0.45	*M* = 0.44, *SD* = 0.34
Inventory Counting	0.83	0.77	*M* = 0.71, *SD* = 0.38
Order picking	0.77	0.71	*M* = 0.75, *SD* = 0.22
Warehouse organisation and administration	0.40	0.29	*M* = 0.30, *SD* = 0.25
Picking systems	0.82	0.86	*M* = 0.82, *SD* = 0.17
Warehouse operations	0.75	0.68	*M* = 0.67, *SD* = 0.31
Truck scale	0.79	0.92	*M* = 0.80, *SD* = 0.31
Logistics	0.56	0.58	*M* = 0.56, *SD* = 0.27
Milk run concept	0.88	0.70	*M* = 0.67, *SD* = 0.45
Pick by light	0.55	0.50	*M* = 0.47, *SD* = 0.42
Pick by voice	0.86	0.6	*M* = 0.57, *SD* = 0.47
Load securing expertise for road vehicles (VDI 2700)	0.71	0.56	*M* = 0.63, *SD* = 0.27
Route planning	0.64	0.44	*M* = 0.40, *SD* = 0.42
Transport and storage technology	0.71	0.42	*M* = 0.40, *SD* = 0.42
Packaging	0.69	0.69	*M* = 0.67, *SD* = 0.18
Shipping	0.75	0.60	*M* = 0.67, *SD* = 0.18
Goods receipt and incoming inspection	0.52	0.50	*M* = 0.51, *SD* = 0.37

Appendix B: ventilation technician, BERUFENET skills classification report

Category	Precision	Recall	F1 Score
Guiding others	0.73	0.62	*M* = 0.68, *SD* = 0.38
Supporting others	0.00	0.00	*M* = 0.00, *SD* = 0.00
Applying health-related skills and competences	0.67	0.62	*M* = 0.56, *SD* = 0.40
Applying cultural skills and competences	0.60	0.30	*M* = 0.30, *SD* = 0.38
Applying environmental skills and competences	0.79	0.79	*M* = 0.71, *SD* = 0.38
Applying entrepreneurial and financial competences	0.45	0.36	*M* = 0.30, *SD* = 0.38
Applying general knowledge	0.80	0.44	*M* = 0.40, *SD* = 0.49
Working with numbers and measurements	0.67	0.86	*M* = 0.71, *SD* = 0.38
Using digital devices and applications	0.76	0.62	*M* = 0.68, *SD* = 0.15
Maintaining a positive attitude	0.45	0.36	*M* = 0.29, *SD* = 0.38
Following ethical codes of conduct	0.44	0.40	*M* = 0.35, *SD* = 0.45
Language proficiency	0.94	1.00	*M* = 0.98, *SD* = 0.06
Working efficiently	0.35	0.33	*M* = 0.32, *SD* = 0.27
Handling and controlling objects and equipment	0.73	0.53	*M* = 0.52, *SD* = 0.37
Handling problems	1.00	0.78	*M* = 0.47, *SD* = 0.48
Communicate	0.75	0.45	*M* = 0.48, *SD* = 0.32
Applying civic and public life competences	0.73	0.57	*M* = 0.58, *SD* = 0.40
Creative and innovative thinking	0.62	0.56	*M* = 0.70, *SD* = 0.46
Planning and organising	0.62	0.45	*M* = 0.47, *SD* = 0.48
Reacting to physical conditions	0.67	0.57	*M* = 0.53, *SD* = 0.37
Processing information, ideas and concepts	0.55	0.50	*M* = 0.43, *SD* = 0.45
Taking a proactive approach	0.64	0.47	*M* = 0.52, *SD* = 0.37
Showing willingness to learn	0.54	0.54	*M* = 0.51, *SD* = 0.44
Collaborating in teams and networks	0.70	0.70	*M* = 0.65, *SD* = 0.45
Working Conditions	0.90	0.64	*M* = 0.67, *SD* = 0.45
Work experience	0.69	0.60	*M* = 0.55, *SD* = 0.40
Job title	0.90	0.82	*M* = 0.83, *SD* = 0.31
Formal Qualification	0.85	0.81	*M* = 0.83, *SD* = 0.15
Other skills	0.65	0.48	*M* = 0.43, *SD* = 0.36
Certificates and Licences	0.88	0.83	*M* = 0.79, *SD* = 0.30
Heating technology	0.52	0.61	*M* = 0.54, *SD* = 0.30
Air conditioning technology	0.64	0.47	*M* = 0.47, *SD* = 0.40
Ventilation technology	0.87	0.72	*M* = 0.73, *SD* = 0.30
Measurement, control and regulation technology	0.52	0.68	*M* = 0.58, *SD* = 0.25
Pipe installation	0.30	0.33	*M* = 0.33, *SD* = 0.32
Sanitary installation	0.72	0.72	*M* = 0.71, *SD* = 0.29
Building services engineering	0.43	0.25	*M* = 0.27, *SD* = 0.42

Assembly (supply technology)	0.99	0.60	*M* = 0.60, *SD* = 0.49
Work preparation	0.75	0.53	*M* = 0.57, *SD* = 0.40
Bathroom planning	0.73	0.62	*M* = 0.55, *SD* = 0.38
Sheet metal processing	0.71	0.71	*M* = 0.63, *SD* = 0.36
Fire protection	0.88	0.88	*M* = 0.83, *SD* = 0.31
Apply insulation	0.67	0.56	*M* = 0.50, *SD* = 0.37
Steam boiler systems	0.64	0.54	*M* = 0.45, *SD* = 0.39
Install and maintain district heating networks	0.73	0.85	*M* = 0.75, *SD* = 0.29
Install and maintain photovoltaic systems	0.99	0.57	*M* = 0.67, *SD* = 0.37
Customer service	0.62	0.42	*M* = 0.43, *SD* = 0.45
Welding and soldering techniques	0.71	0.74	*M* = 0.71, *SD* = 0.18
Welding and soldering techniques	0.57	0.38	*M* = 0.38, *SD* = 0.35
Use maintenance/inventory management software (CMMS)	0.64	0.54	*M* = 0.52, *SD* = 0.37
Monitor, maintain and install water networks	0.92	0.79	*M* = 0.83, *SD* = 0.31
Install and maintain biomass heating systems	0.88	0.50	*M* = 0.50, *SD* = 0.43
Install and maintain fuel cell heating systems	0.90	0.75	*M* = 0.73, *SD* = 0.39
Condensing technology	0.88	0.64	*M* = 0.63, *SD* = 0.43
Assemble and maintain water supply systems	0.57	0.80	*M* = 0.63, *SD* = 0.37
Welding certification	0.80	0.67	*M* = 0.65, *SD* = 0.45
Install and maintain combined heat and power plants	0.70	0.78	*M* = 0.62, *SD* = 0.43
Quality control and assurance	0.71	0.62	*M* = 0.43, *SD* = 0.45
Rainwater management	0.79	0.79	*M* = 0.81, *SD* = 0.18
Install and maintain smart home systems	0.57	0.57	*M* = 0.51, *SD* = 0.31
Solar sorption cooling systems	0.99	0.80	*M* = 0.80, *SD* = 0.40
Install and maintain solar thermal systems	0.80	0.62	*M* = 0.62, *SD* = 0.43
Certification under §5 Chemical Climate Protection Regulation	0.99	0.99	*M* = 0.60, *SD* = 0.49
Expertise in boiler plant operation	0.71	9.83	*M* = 0.50, *SD* = 0.50
Install and maintain heat pump systems	0.99	0.62	*M* = 0.57, *SD* = 0.47

Appendix C: Classification Report Pool Size Warehouse logistics operator

Category	Precision	Recall	F1 Score
No formal qualification	0.80	0.94	0.86
Work experience	0.93	0.88	0.90
warehouse clerk (2-year vocational degree)	0.88	0.92	0.90
Warehouse logistics specialist (3-year vocational degree)	0.89	0.87	0.88
Acceptance of alternative training	0.86	0.75	0.80
Work experience as a substitute for formal training	0.55	0.86	0.67

Appendix D: Classification Report Pool Size Ventilation Technicians

Category	Precision	Recall	F1 Score
No formal qualification	0.69	0.59	0.64
Work experience	0.39	0.39	0.39
Ventilation technician	0.48	0.79	0.59
Acceptance of alternative training	0.62	0.68	0.65
Work experience as a substitute for formal training	0.43	0.20	0.27

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