ASSESSING THE DEGREE OF SKILL INTERSECTION AND TRANSFERABILITY AMONG OCCUPATIONAL GROUPS: EVIDENCE FROM A VACANCY ANALYSIS IN UKRAINE

by

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LIST OF ABBREVIATIONS

ISCO International Standard Classification of Occupation

ESCO European Skills, Competences, Qualifications and Occupations

OECD Organisation for Economic Co-operation and Development

IDP Internally displaced person

ICT Information and communication technologies

OSHC Occupation-specific human capital

O*NET Occupational Information Network

KSA Knowledge, skills, and abilities

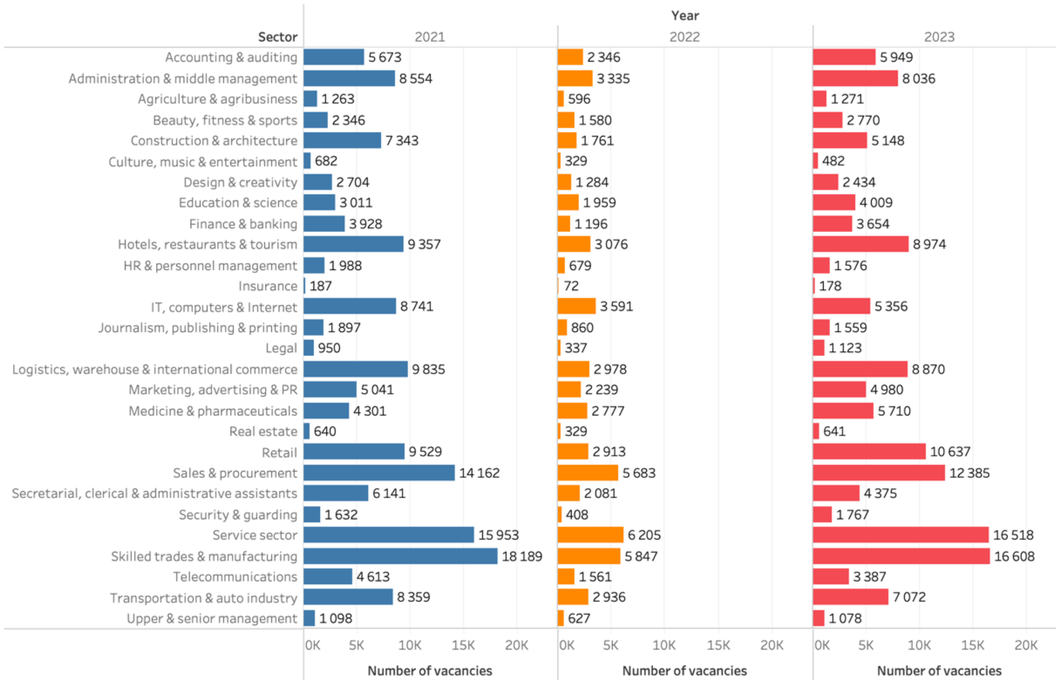
HAC Hierarchical agglomerative clustering

CHAPTER 1. INTRODUCTION

Since the beginning of the full-scale invasion, the labor market in Ukraine faced different changes. One of its biggest challenges is a contraction of numerous sectors due to various reasons such as loss of productive workers, destruction of firms' infrastructure, and occupation of territories by Russia.

After February 2022, the demand for workers across different sectors decreased significantly. As Figure 1 shows, all sectors experienced a very dramatic decline in 2022 in the number of vacancies compared to 2021 values. There are niches, such as IT and Culture, music, and entertainment, where the number of vacancies shrank by more than 50% in 2022. In 2023, they managed to achieve only up to 70% of the volume of vacancies in 2021. The most harmed sectors are Finance and Banking, Logistics, Warehouse and international commerce, and Retail. Despite that, these sectors managed to recover much better, as they have more than 70% vacancies compared to the 2021 volume.

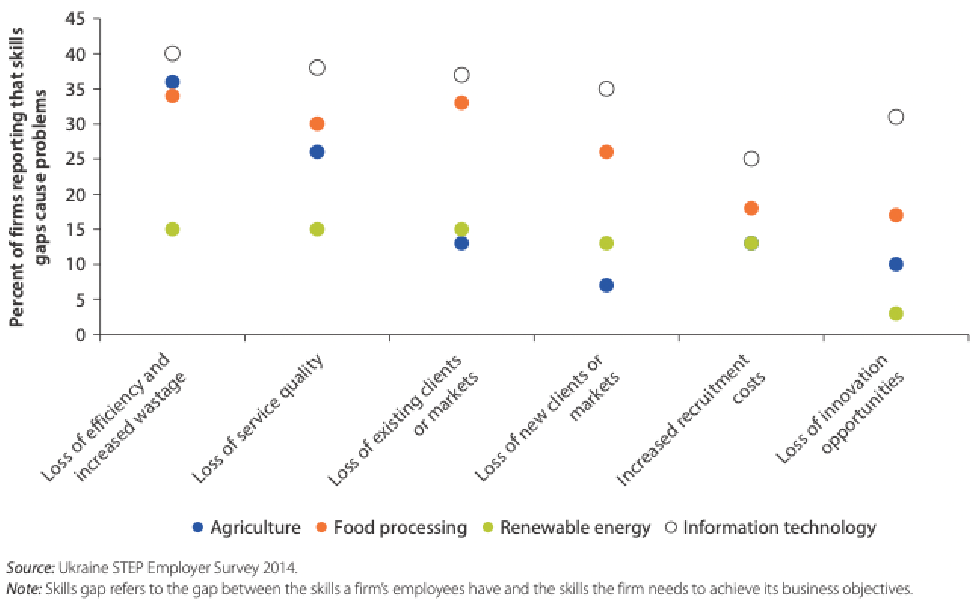
Figure 1. Distribution of vacancies per Work.ua categories



Source: Work.ua (data is taken for August only for all years)

On the one hand, sectors with strong recovery are very important for the Ukrainian economy, and they seek very fast employment to fulfill their recently recovered capacities. On the other hand, having a bigger number of vacancies doesn't necessarily mean that this demand will be matched with a supply of adequately skilled workers in the same way as it was in 2021. Even before the full-scale invasion, businesses reported that they suffered losses because of gaps in the skills of their employees. According to Del Carpio et al. (2017), different skills gaps cause different volumes of losses depending on the sector. Even though the values vary from sector to sector, on average, from 20% to 30% of firms mentioned that they had experienced different types of losses because of skills gaps (Figure 2).

Figure 2. Problems Related to Skills Gaps Cited by Ukrainian Firms in Four Key Sectors



Source: Del Carpio et al. (2017)

In addition to the existing issues of skills gaps, the labor market in Ukraine faces new challenges. According to the Ministry of Reintegration[1], the number of IDPs ranges from 4.3 to 7 million people, which is approximately 1/6 of all Ukrainian population. The question of their reintegration into the host communities and to the local labor market is very important nowadays. Hence, to keep the Ukrainian economy employed, it is crucial to understand which sectors IDPs can look at, considering their background, abilities, knowledge, and skills.

One more important challenge is the reintegration of war veterans. After stopping serving in the Armored Forces, the ex-militaries will face the same issues as IDPs, because

[1] Number of IDPs: https://www.slovoidilo.ua/2023/02/07/novyna/suspilstvo/minreintehracziyi-rozpovily-skilky-ukrayini-zareyestrovano-vnutrishno-peremishhenyx-osib

of a loss of knowledge and experience and contraction of niches they worked in before serving.

All cases enlisted above signify the importance of talking about an efficient transfer between occupations. Either job seekers who couldn't find a job in contracted sectors or businesses searching for very fast employment need to know which other spheres suit their needs well.

The research question of this paper is what the level of intersection and transferability of skills between different occupations is.

To give a precise answer to the question above, this paper aims to define how similar occupations are based on skills demanded in vacancies. Subsequently, the cluster analysis groups the occupations based on their similarities.

The data on skills is gathered by web scrapping vacancies from Work.ua, the most visited job platform in Ukraine[2]. Compared to its competitors, this platform allows one to get a wider range of occupations with high and medium-skilled workers.

The paper continues with the following structure. Chapter 2 overviews the literature related to the definition and estimation of transferability of skills. Chapter 3 describes the methodology used to estimate the transferability of skills and goes over the clusters creation. Chapter 4 aims to describe the dataset used for this research. Chapter 5 focuses on the results of clustering analysis and the practical use of the created clusters. Chapter 6 summarizes all the previous parts and focuses on the implications for individuals, businesses, and government, and gives ideas for further discussions.

[2] TOP visited Jobs and Employment websites: https://www.similarweb.com/top-websites/ukraine/jobs-and-career/jobs-and-employment/

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

This section represents the articles and studies that provide a better understanding of the skills demand in the labor market in Ukraine, the definition of skills transferability, and the common approaches to measuring the transferability of skills.

2.1 The Skills Categorization.

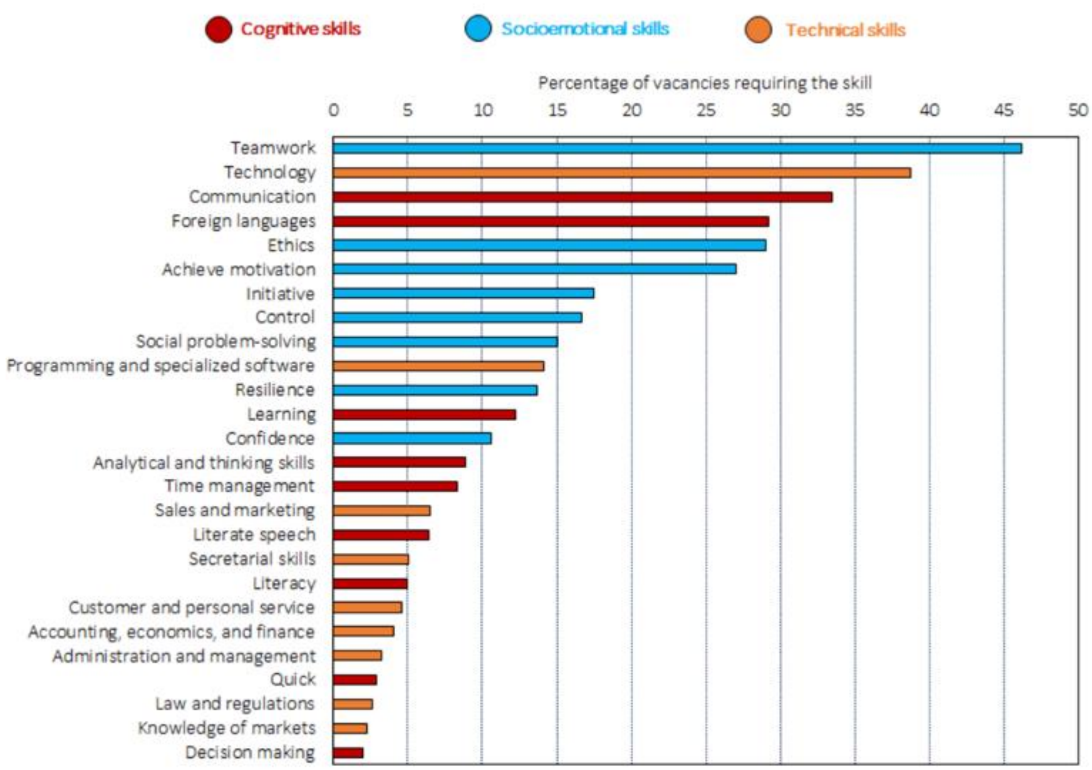
There are numerous ways to categorize the skills in the labor market depending on the goals of the research. In OECD (2015), the authors discuss the definition and categorization of skills that employers require most. There are three sets of skills defined in this report:

1. Cognitive – foundational skills that give the ability to do simple reasoning and basic cognitive operations. Examples: writing, reading, speaking, and problem-solving;
2. Socio-emotional, also referred to as soft skills, include interaction with other people and self-management. Examples: emotional intelligence, cooperation with the team, leadership, and mentoring;
3. Technical – job-specific hard skills, such as physical condition and computer usage. These skills differ for job positions, so even the same occupation in two companies might require different use of these skills.

For employers, these skill sets have different importance. Kureková et al. (2017) examine how often employers mention different skills depending on the occupation across Europe. Researchers found out that employers mostly stress non-cognitive skills. The authors also signify the diversity of demanded skills across countries. The form in which a country's labor market shows its need for skills is influenced by domestic organizations and systems. Hence, it is important to distinguish the Ukrainian context and not mix it with the other county-specific skills requirements.

The assessment of different skills demanded was researched by Muller and Santos (2019). This paper analyzes vacancies posted on Head Hunter's website to assess the demand for skills for medium and high-skilled workers. The authors signify that employers in Ukraine are primarily looking for a mix of advanced cognitive, socioemotional, and technical skills. However, one can notice that in Figure 3, the share of the socio-emotional skills in the vacancies is higher than for the other groups of skills, which could lead to a wrong conclusion that socio-emotional skills are more important than others. In other words, if an employer mentions 10 different skills in a nurse vacancy, there could be one skill mentioned in a vacancy related to medical knowledge, but its absence is much more critical than the absence of some of the other 9 skills for employing some job-seeker.

Figure 3. Most demanded socio-emotional, cognitive, and technical skills in Ukraine, 2019



Source: Muller and Santos (2019)

A very important point coming from Muller and Santos (2019) research is that employers mostly seek skills rather than degrees from universities. It means that while analyzing skills from vacancies, scrapping education will not give much value to the question of the use of skills at work. That is because mentioning a specific degree in vacancy cannot give information about which skills obtained from a university or some other program are needed exactly.

2.2 Transferability of skills

As mentioned in the European Commission (2011) report, transferable skills are the skills that can be applied to any job or task, regardless of where they were first acquired. The more general skill, the more transferable it is, and vice versa. However, it doesn't mean that some cognitive, socio-emotional, and technical skills are fully transferable while others are not. The European Commission (2011) report says that nowadays, all the skills are transferable to some extent. In other words, transferability is more like a scale that varies from low to high, considering the job specifics and market conditions.

If workers use skills with low transferability, to successfully apply for another job, they need to retrain. The amount of skills an individual needs to acquire depends on two factors: the extent of transferability of the skills they have already used and the skills demanded by a new position they have not used before. If a new position requires very specific technical skills – their degree of transferability will be low, and they could be achieved only by some specific education, or at similar work.

2.4 Transferability estimation approaches

The studies on estimating the transferability of skills are rather scarce. Typically, such studies use survey data or benchmarks. As of the time of writing this research, there are no such benchmarks available for Ukraine. The closest possible survey was conducted in

2014 and is not relevant to this study, considering major changes in the labor market since that time. However, with the development of informational technologies, the web scraping approach became more available and could be used for skills-related task estimations. Applying the web-scrapped data from Ukrainian job platforms and estimation methodologies of foreign researchers could shed some light on the topic.

Shaw (1984) proposes to distinguish skills into two types: general and job-specific skills. Based on the U.S. National Longitudinal Survey of Young Men (1975), the researcher mainly focuses on the probability of switching between some occupation i to some occupation j based on the skill set of an individual. Based on these probabilities, Shaw proposed an algorithm (1) that calculates the distance between occupations i and j:

$$D^{ij} = \sum_{k=1}^{J} |P^{ik} - P^{jk}| = (P^{ij} + P^{ji}) - (P^{ii} + P^{jj}) + \sum_{k=1}^{J} |P^{ik} - P^{jk}| \quad (1)$$

where P^{ij} is the probability of moving from some occupation i to some occupation j.

As Shaw says, the obtained distance correlates with a transferability measure t_{ij} (2) of the OSHC (occupation-specific human capital) from occupation i and some occupation j. It yields that the higher the transferability of skills in occupations i and j, the higher the probability of switching between these occupations:

$$t_{ij} = \frac{OSHC_i \cap OSHC_j}{OSHC_i} \quad (2)$$

One more issue coming from Show's research is that the declining opportunities for investment in occupation i will increase a desire to move to occupation j, where a move is associated with great new investment in occupation-specific skills. In such case, switching from occupation j to occupation i will be more likable than shifting from occupation i to occupation j. It yields that workers prefer to get a higher-skilled occupation rather than shifting to a lower-skilled one.

However, Shaw's approach has some limitations. Nawakitphaitoon and Ormiston (2016) note, the Shaw's approach concentrates a lot on the market itself. In the case of Ukraine, there might be a bias coming from the market limitations, such as supply or demand shortages, that lead to a higher and lower demand for some specific occupations. Researchers also note that Shaw's approach does not account for a disproportional switch between occupations, such that moving from occupation i to occupation j will not take the same time as moving from occupation j to occupation i. For example, moving from customer support to a doctor will take longer than vice versa. The skills needed to be gained by doctors could be achieved by studying only at specific universities and have low transferability, while the skills needed for customer support could be achieved much faster.

The Ormiston (2014) research uses a methodology that corrects the points mentioned above. Based on O*NET data, Ormiston investigates how well an individual can transfer a set of KSA (knowledge, skills, abilities) used at occupation i to occupation j. For that purpose, the researcher derived two measures: Transferability Rate and Qualification Rate.

- $t_{i,j}$ – transferability rate evaluates how well the OSHC from occupation i can be transferred to occupation j. A low transferability rate typically means that an individual, while deciding on switching from occupation i to occupation j can transfer a low amount of KSA (Knowledge, skills, and abilities) and vice versa.
- $q_{i,j}$ – qualification rate, which describes how much work in the occupation i qualifies an individual for employment in the occupation j. In other words, it is a proportion of OSHC required in occupation j that can be achieved by working in occupation i.

Based on the combinations of these two measures, Ormiston (2014) defines four cases of switching between occupations:

- Low Transferability rate, High qualification rate, - usually happens when workers face a downward switch when a person is overqualified for a specific job (i.e. nurse to a personal aide worker).
- Low transferability rate, Low qualification rate – usually happens when workers switch between very dissimilar occupations (i.e. sales worker to machine plant operator)
- High transferability rate, High qualification rate – appear when there is a case of a switch between very close occupations (i.e. sales worker to customer service worker)
- High transferability rate, Low qualification rate – usually happen in case of promotions, when all skills from occupation i suit well to occupation j, but not all the needed skills for occupation j were present in occupation i (i.e. sales worker to head of sales department).

The limitation of Ormiston's Approach for the Ukrainian context is related to the use of O*NET data. The O*NET is usually used as a benchmark completed by analysts and tailored only to the U.S. labor market. Using O*NET does not give any information about the actual supply and use of skills at work (Handel., 2016), and as of the time of writing this study, there is no such benchmark for European or Ukrainian realities.

There is another issue that Nawakitphaitoon (2014) points out. The author states that the transferability approaches should have specific weights. As an example, the researcher mentions the "medicine and dentistry" knowledge category that is the most important for surgeons and physicians. Without this category, similarities with other occupations are unimportant, and an individual simply cannot conduct the transfer because of a lack of this knowledge category.

Both studies mentioned above provide coefficients that indicate transferability between different occupations. The clustering approach helps identify the groups of occupations close to each other, such that, Khalaf et al. (2021) investigated the transferability of skills of North Carolina Tobacco Manufacturing Skillshed by using the hierarchical agglomerative clustering (HAC) method. Based on knowledge, activities at work, capacities, and job area, the researchers grouped 77 occupations into four clusters. The study provides a heatmap that describes the level of complexity of transition between occupations grouped in some of the four clusters. It shows that the more technical occupations grouped within one cluster, the harder it is to transfer within the same cluster. It aligns with the fact mentioned in the 2.2 section, that the less general skills are, the less transferable they are.

To sum up, the transferability of skills has become an important topic in foreign studies, but it has not been well studied in Ukraine so far. The biggest challenge in this topic for Ukrainian researchers is the lack of data. As of the time of writing this study, web scrapping is the only available method for accessing the transferability of skills. However, this approach has its own limitations, described in the following chapter.

CHAPTER 3. METHODOLOGY

The transferability of skills in the Ukrainian labor market is assessed in two steps. The first step is to identify the degree of similarities between occupations based on the analysis of skills demanded in vacancies, which are scrapped from the job platform Work.ua. The second step is a clustering analysis based on the occupations' similarities. Before this analysis, occupations and skills have been grouped in line with international classifications. Namely, the ISCO-08 (International Standard Classification of Occupations, 2008). To classify skills into groups, the ESCO classification is used.

3.1 ISCO groups similarities

In this step, the measurement of similarities is conducted. This process is divided into two parts. The first part is concentrated on measuring the frequency of mentioning all ESCO skills across all ISCO categories. This is addressed by calculating a sum (3) of each skill category within the ISCO group.

$$\mathrm{A}(o, s) = \sum_{i=1}^{n} j_i \tag{3}$$

where

A – a vector of some o ISCO two-digit group, where s are the sum of mentions of some ESCO skill group in vacancies.

j_i – a dummy variable that is 1 if some ESCO skill was mentioned in some i vacancy and 0 if not. It only accounts for unique mentions of ESCO skill groups, such that if some ESCO skill group was mentioned twice in some vacancy, it is still counted as 1.

n – number of vacancies per o occupation.

After computing the sum of each ESCO skill group within each ISCO category, the M matrix is created, where rows are the ISCO occupations and columns are the ESCO skill categories with a sum of mentions of these categories.

For the further investigation of similarities of vectors from matrix M, the cosine similarity (4) measure is applied. This measure finds the similarity between two row vectors based on their inner product space. In such a way, the cosine of the angle between some two vectors from matrix M is calculated.

$$S(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \cdot \|B\|} = \frac{\sum_{i=1}^{n} A_i \cdot \sum_{i=1}^{n} B_i}{\sqrt{\sum_{i=1}^{n} A_i^2 \cdot \sum_{i=1}^{n} B_i^2}} \tag{4}$$

where

A – a vector that represents some occupation with a sum of the skills within the occupation.

B – a vector that represents different from vector's A occupation with a sum of skills within that occupation.

There are two advantages of cosine similarity compared to Euclidian distance, a more classical way to measure the distance between vectors.

- The first one is that the cosine similarity disregards a vector's size (Vl Frederick, 2023). In this case, it is crucial because even though the data is scrapped across oblast centers and sectors represented at Work.ua, because of job platform and labor market specifics, there are ISCO-08 occupations that have more vacancies than others.
- The second one refers to the interpretation of the results. Cosine similarity results are always bounded between -1 and 1 values, while the Euclidian distance is an absolute measure, making the cosine similarity more suitable for cross-occupational comparison.

3.2 Defining clusters

After the previous step, the identical matrix A(i, j) is created, where i and j are ISCO two-digit occupations and some (i, j) element from this matrix is a similarity between occupation i and occupation j. Based on this matrix, bottom-up hierarchical clustering, or so-called Agglomerative clustering, is selected as a method of cluster creation.

Here is a description of the algorithm based on Introduction to Statistical Learning (2023):

1. In the first part of this bottom-up approach, each element (i, j) of the matrix A is treated as a separate cluster. With n observations and a measure of Euclidean distance, the pairwise distance between similarities is calculated.

2. For $i = \text{n},\ \text{n} - 1, \dots 2$:

   (a) Firstly, across all clusters, the pair of two clusters with the lowest distance is found. These two clusters are merged into one group and, in the next step, will be treated as one cluster. The similarity between these two clusters is indicated by the height in the dendrogram.

   (b) Secondly, the new pairwise inter-cluster distances are computed among the $i - 1$ remaining clusters.

The algorithm proceeds till the moment only two clusters are left. The distance between all clusters and the process of grouping different elements of matrix A is visually represented on the dendrogram, where the X axis stands for the matrix A elements and the Y axis stands for the height between divisions into clusters. Each additional point at this scale is associated with the next level of hierarchical clustering. As it is noted in An Introduction to Information Retrieval (2009), there is no predetermined number of clusters required for hierarchical agglomerative clustering. Fixing some value y at this scale results in a specific number of created clusters. Consequently, the fixed value y is a threshold for cluster creation.

3.3 Expected outcome

We can expect that two-digit ISCO categories, that share the same first digit, such as Production and Specialized Services Managers and Hospitality, Retail and Other Services Managers, will be closer to each other, rather than radically different categories, such as Medical Workers and Drivers.

ISCO categorization by design creates different groups based on how much time people need to earn these occupations. Obviously, workers from such occupations also tend to use similar clusters of skills at work, but not the same. Moreover, because of applying Ukrainian context and Work.ua specifications there might be different results.

3.4 Methodology limitations

This methodology also brings some limitations that should be mentioned.

- Even though Work.ua is the most visited job platform in Ukraine, it still does not give an exhaustive information about the labor market, so that the web scrapped vacancies should be treated as only a part of the population of all demand for workers.

- This research could capture some seasonal patterns because of the time range of scrapping (July 2023 – September 2023).

- As in Shaw's (1984) methodology, this algorithm does not account for disproportional transferability, as moving from occupation i to occupation j is not the same as shifting between occupations j and i. Hence, the final results cannot directly estimate how long it will take to switch between occupations, but evaluate the interaction of skills between occupations only.

- This approach relies on the market but does not account for its limitations and barriers, such as educational or experience barriers. For example, it does not account that people who become doctors need to spend 5 years to study the relevant studies, while to become a programmer, it is often fine to complete some courses on the Internet.

- There is no relevance score in this approach. It is assumed that if an employer mentions some skills $s1$ and $s2$ in a vacancy, for them both skills play the same role in the process of deciding on hiring candidates. However, for example, if a job-seeker applies for a nurse, so for them a lack of medical skills is more critical than a lack of some specific soft skills.

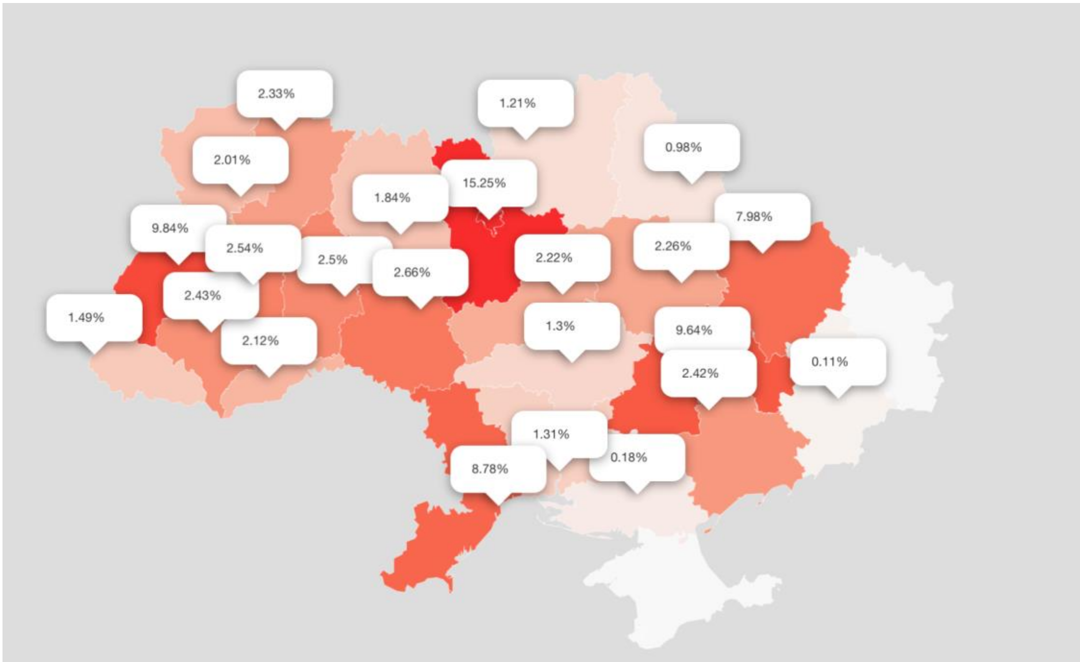
CHAPTER 4. DATA

The data for this research is web-scraped from the Ukrainian labor market platform Work.ua. The unit of observation is a unique vacancy published on this website. The data for this research was gathered starting from June 10th to September 10th, 2023, and contains the following variables:

1. Primary Key – unique Vacancy Identification.
2. The title of the occupation.
3. Oblast center: a categorical variable that shows in which oblast center an employer is located.
4. Skills set: a set of skills mentioned in the vacancy.

Overall, there are 12995 vacancies scrapped within this period. The data was scrapped for all Ukrainian oblast centers except temporarily occupied territories. In Donetsk oblast, the regional center is temporarily uncontrolled, so the two major cities, Kramatorsk and Slovyansk, are used for scrapping vacancies instead. Unfortunately, there are no vacancies for Luhansk oblast and Crimea due to their occupation by Russia. According to Figure 4, the biggest share of captured vacancies belongs to Dnipro, Kyiv, and Lviv oblasts.

Figure 4. Distribution of scrapped data among oblast centers in Ukraine.

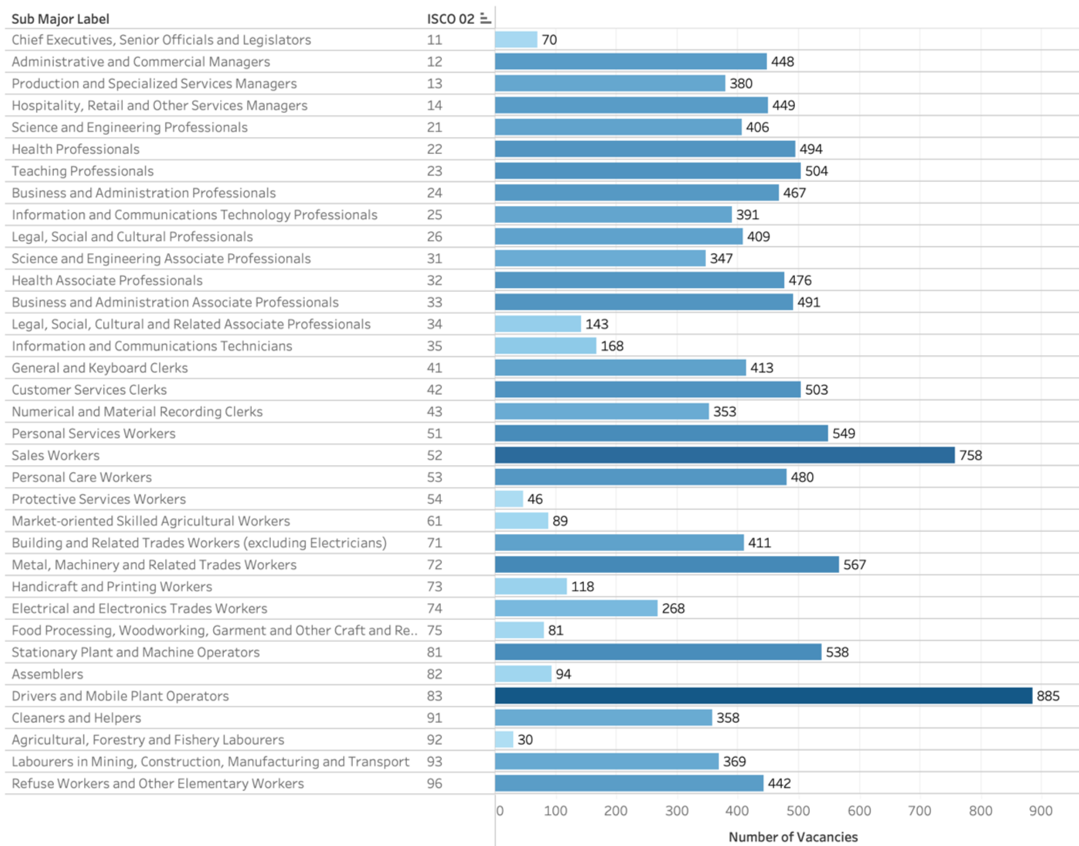


Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

2.1 ISCO two-digit categories

ISCO 08 has a 4-digit system, starting with 1-9 digits assigned to basic and broad categories. Adding one extra digit is associated with a more detailed drill down in the original category. Figure 5 represents the distribution of vacancies on the ISCO two-digit level. In the case of the scrapped sample of vacancies, a one-digit ISCO 08 categorization would be too broad to derive insightful results, while three-digit categories would not have enough observations to provide valid results. Hence, a two-digit drill down is the best choice for this research.

Figure 5. Distribution of vacancies among ISCO two-digit categories.



Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

Even at the two-digit level, there are occupations that have a small number of scrapped vacancies. Such ISCO groups cannot be very trustworthy, because there might be some very specific skills captured by these vacancies that do not represent the whole occupation well or lead to wrong results in clustering analysis. Hence, all the occupations with less than 100 vacancies are removed. From Figure 5, these occupations ISCO codes are 11, 54, 61, 75, 82, and 92.

There are also other groups from ISCO categories that are not presented on the Figure 5, as did not get into the web scraping sample because of a very small number of vacancies present on Work.ua. Examples of such occupations are Market-oriented Skilled Forestry, Fishery and Hunting Workers, Subsistence Farmers, Fishers, Hunters and Gatherers, Food Preparation Assistants, and Street and Related Sales and Services Workers, etc.

It is important to note, that despite the data being collected across different occupations and oblast centers, acquiring such data from any job platform gives only a partial picture of the Ukrainian labor market.

2.2 ESCO Skills Categories.

There are 108 different skills available in the ESCO database on a two-digit level. This level is selected for the same purpose as the ISCO two-digit level. However, even this drill down includes very specific skills that could not be captured because of absence of vacancies that require such skills. Examples: operating watercraft or operating aircraft skills. On the other hand, there are also skills, that are simply not used to be mentioned in vacancies, such as general knowledge or literacy. Keeping these skills will result in skewing the results of cross-occupational analysis, as having the same sum of skill equal to 0 across all occupations will automatically make all occupations closer to each other. Hence, from these 108 different skill groups, the categories mentioned less than 10 times in all vacancies are removed.

5.1. Similarity matrix

Following the approach described in Chapter 3.1, an identical matrix 29x29 is created, where rows and columns are ISCO two-digit categories, and the values are the similarities between occupations (see Table A.1 in Appendix). Table 1 provides the mean of similarity indices across ISCO codes. It shows that the average cosine similarity of all occupations is 0.78, which is an indicator that there are lots of similar points between occupations.

Table 1: Mean similarities across ISCO codes

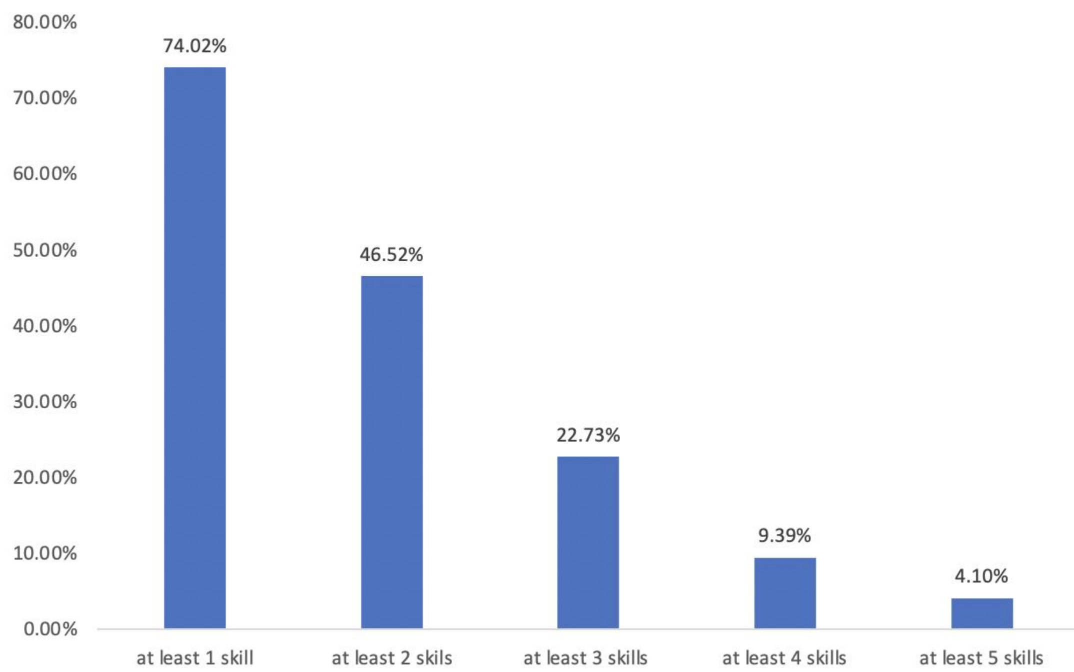
ISCO code	Mean Similarity	ISCO code	Mean Similarity
12	0.82	**42**	0.79
13	0.81	**43**	0.83
14	0.81	**51**	0.81
21	0.78	**52**	0.79
22	0.70	**53**	0.85
23	0.65	**71**	0.81
24	0.78	**72**	0.76
25	0.67	**73**	0.79
26	0.78	**74**	0.81
31	0.84	**81**	0.80
32	0.76	**83**	0.75
33	0.84	**91**	0.83
34	0.74	**93**	0.82
35	0.76	**96**	0.70
41	0.85		

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

Such a high similarity between occupations is driven by two facts. First, a very high percentage of skills demanded belongs to working with others, working efficiently, communicating, using more than one language, following ethical code, etc. These skills are classified by Hart (2021) as transversal. Such skills and abilities are important for any type of work and do not belong to any specific occupation.

Transversal skills tend to be very popular across all the ISCO groups. As shown in Figure 6, 74.02% of vacancies have at least one unique transversal skill mentioned.

Figure 6: Percentage of at least X transversal skills in vacancies



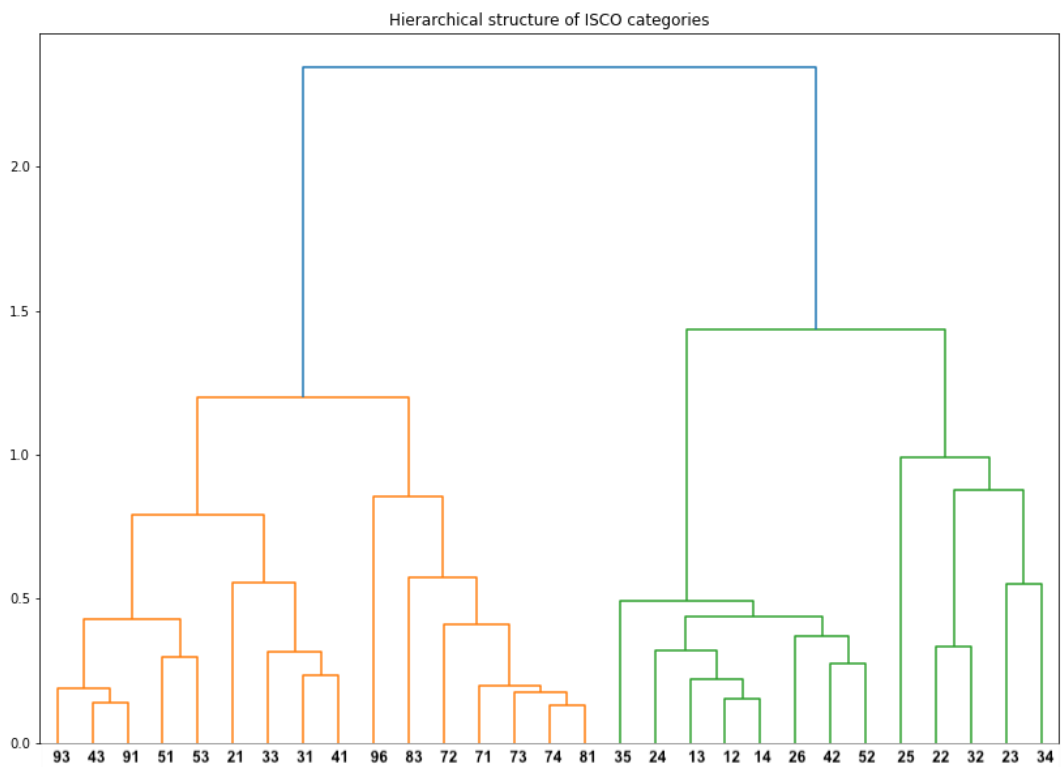
Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

The second explanation for very high similarities between occupations is that there are many specific skill groups, such as forestry skills or handling animals, that are mentioned in very specific ISCO categories but almost not mentioned in others, which makes the other ISCO groups closer to each other.

5.2. Dendrogram and Threshold Selection

Following the algorithm described in Chapter 3.2, the dendrogram is created. The height between the dendrogram nodes shown in Figure 7 represents the distance between the ISCO two-digit categories. At the range of 0.52 to 0.77, the clusters do not change at all, while a 0.51 value results in 10 clusters, which already makes the results less interpretable. To keep interpretative results, the height is fixed at 0.7, and all the clusters below are cut off. As a result of setting this specific threshold, the 8 clusters are created.

Figure 7: Dendrogram of ISCO two-digit occupations



Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

5.3. Clusters

This subpart aims to describe the created clusters. All clusters are named according to the occupations inside them. All descriptions of clusters contain explanations and tables at the bottom except clusters with only one occupation inside. The tables consist of three parts: ISCO two-digit codes, an Explanation of ISCO codes, and a similarity matrix between occupations that belong to the cluster.

a) Industrial and Mechanical Trades Cluster

The first cluster combines occupations with workers who mostly work with some specific sort of machine and is shown in Table 2. This is a straightforward group that aligns with ISCO specifications pretty well, as all 7-digit occupations belong to this group. Apart from the transversal skills, the most demanded skills in this cluster are driving vehicles, using hand tools, manufacturing and processing, and engineering or engineering trades. However, these skills are very job-specific, so depending on the occupation, it will take some retraining to switch between ISCO groups.

Table 2. Similarities between ISCO occupations from Industrial and Mechanical Trades Cluster.

ISCO	Explanation		83	81	74	73	72	71
83	Drivers and Mobile Plant Operators		1.00	0.81	0.79	0.80	0.79	0.87
81	Stationary Plant and Machine Operators		0.81	1.00	0.96	0.95	0.90	0.95
74	Electrical and Electronics Trades Workers		0.79	0.96	1.00	0.96	0.89	0.94
73	Handicraft and Printing Workers		0.80	0.95	0.96	1.00	0.91	0.95
72	Metal, Machinery and Related Trades Workers		0.79	0.90	0.89	0.91	1.00	0.95
71	Building and Related Trades Workers		0.87	0.95	0.94	0.95	0.95	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

b) Clerical and Scientific Professions Cluster

The cluster presented in Table 3 accumulates workers from the Clerical and Scientific Professions from ISCO categories. The most commonly demanded skill groups in this cluster are using digital tools for collaboration, content creation, and documenting and recording information. Such skill groups could stand for different purposes depending on the task, such that for General Keyboard Clerks, these skills are mostly denoted as "confident PC user" and "using Word for documentation", while for the other groups, these skill groups are driven by more complicated tasks. Additionally, it is because of the specifics of today's labor market, that a high share of the ISCO 41 group belongs to office managers and secretaries. Their demanded skills are very close to what ISCO 33 vacancies require.

Table 3. Similarities between ISCO occupations from Clerical and Scientific Professions Cluster.

ISCO	Explanation		41	21	31	33
41	General and Keyboard Clerks		1.00	0.87	0.92	0.92
21	Science and Engineering Professionals		0.87	1.00	0.92	0.82
31	Science and Engineering Associate Professionals		0.92	0.92	1.00	0.90
33	Business and Administration Associate Professionals		0.92	0.82	0.90	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

c) Management and Service Industry Cluster

This cluster combines different management occupations, as well as Service Industry Professionals, presented in Table 4. Managers were combined with a bit lower-skilled occupations, such as Sales Workers and Customer Service Clerks, because of the very high importance of socio-emotional skills, such as communicating, working with others, negotiating, etc., for both ISCO groups. Also, from the Figure 5, Sales workers is the second biggest occupation by number of vacancies. Moreover, the Manager of the Sales Department is the most popular title among Administrative and Commercial Managers. This fact drives a big share of promoting, selling, and purchasing skills demanded among managers and, as a result, a high similarity between Sales Workers and Administrative and Commercial Managers.

However, there will not be an easy transfer between these groups, because Managers are usually very experienced employees who, apart from the soft skills demanded, also require more experience in organizational skills and leading and motivational skills.

Table 4. Similarities between ISCO occupations from Management and Service Industry Cluster.

ISCO	Explanation		52	42	35	12	26	24	14	13
52	Sales Workers		1.00	0.87	0.88	0.93	0.82	0.84	0.93	0.86
42	Customer Services Clerks		0.87	1.00	0.85	0.91	0.86	0.85	0.85	0.85
35	Information and Communications Technicians		0.88	0.85	1.00	0.86	0.78	0.86	0.87	0.85
12	Administrative and Commercial Managers		0.93	0.91	0.86	1.00	0.90	0.93	0.97	0.97
26	Legal, Social and Cultural Professionals		0.82	0.86	0.78	0.90	1.00	0.87	0.85	0.85
24	Business and Administration Professionals		0.84	0.85	0.86	0.93	0.87	1.00	0.89	0.93
14	Hospitality, Retail and Other Services Managers		0.93	0.85	0.87	0.97	0.85	0.89	1.00	0.95
13	Production and Specialized Services Managers		0.86	0.85	0.85	0.97	0.85	0.93	0.95	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

d) Teaching and Social Associate Professionals Cluster

The Teaching and Social Associate Professionals Cluster is presented in Table 5. This cluster combines two different groups of workers: Teaching Professionals and Legal, Social, Cultural, and Related Associate Professionals. Based on Table 1, these groups are pretty different from the other ISCO categories. The reason is that the most popular skill among ISCO 23 and ISCO 34 groups is teaching and training, which is present in 78% and 50% of vacancies from these groups, respectively. Such a high percentage of these skills required for the ISCO 34 group is explained by the fact that 64% of the vacancies in this group belong to occupations related to various sports coaching activities, such as fitness or football coaches.

Table 5. Similarities between ISCO occupations from Teaching and Social Associate Professionals Cluster.

ISCO	Explanation		23	34
23	Teaching Professionals		1.00	0.93
34	Legal, Social, Cultural and Related Associate Professionals		0.93	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

e) ICT Professionals Cluster

This cluster includes only one ISCO category - ICT professions. This ISCO 02 category has a big share of very specific IT skills, such as setting up and protecting computer systems (mentioned in 29% of vacancies) and programming computer systems (mentioned in 28% of vacancies). Even though there are 4 soft Skills listed in the TOP 10 mentioned skills in vacancies, the others are very specific for this field. However, this cluster, based on common knowledge, is still easily attractable by Workers from the ICT technician occupations.

f) Health Care Cluster

This cluster has only two ISCO categories, which are very specific in terms of demanded skills, such as providing health care or medical treatment, which is mentioned in 53% and 43% of vacancies from ISCO 22 and ISCO 32 groups, respectively. These groups are shown in Table 6 and are very similar in terms of the skill sets required; however, in the case of switching from Associate Professionals to Professionals, retraining is required as workers could become Professionals in this sphere only after completing specific education. At the same time, Associate professionals could find their jobs after achieving tertiary education.

Table 6. Similarities between ISCO occupations from the Health Care Cluster.

ISCO	Explanation		**32**	**22**
32	Health Associate Professionals		1.00	0.96
22	Health Professionals		0.96	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

g) Refuse Workers Cluster

As the ICT Professionals Cluster, The Refuse Workers Cluster includes only one ISCO category. That is because almost the only skills that are mentioned in this group are soft skills and transversal skills. Only one out of the TOP 10 skill groups does not belong to the soft skills group categories. This skill group is cleaning and appears in only

7% of vacancies. Having developed only soft skills makes it very hard for workers from this cluster to switch without complex retraining.

h) Manual Labor and Caregiving Services Cluster

The cluster presented in Table 7 includes Manual Labor workers merged with Caregiving Services Workers. This group is also categorized as a cluster with a very high percentage of soft skills. However, there are also some job-specific skills that define their uniqueness, such that the Personal Services Workers tend to have a high share of preparing and serving food and drinks, while the ISCO 43 group uses digital tools for collaboration, which is a pretty distinct requirement in this cluster. In general, switching from one occupation to another inside this cluster will not take much time, as employers mainly stress soft and transversal skills in vacancies, except for switching to Numerical and Material Recording Clerks, as this occupation requires some basic ICT skills.

Table 7. Similarities between ISCO occupations from Manual Labor and Caregiving Services Cluster.

ISCO	Explanation		93	43	51	53	91
93	Labourers in Mining, Construction, Manufacturing		1.00	0.98	0.89	0.91	0.96
43	Numerical and Material Recording Clerks		0.98	1.00	0.89	0.92	0.96
51	Personal Services Workers		0.89	0.89	1.00	0.91	0.95
53	Personal Care Workers		0.91	0.92	0.91	1.00	0.94
91	Cleaners and Helpers		0.96	0.96	0.95	0.94	1.00

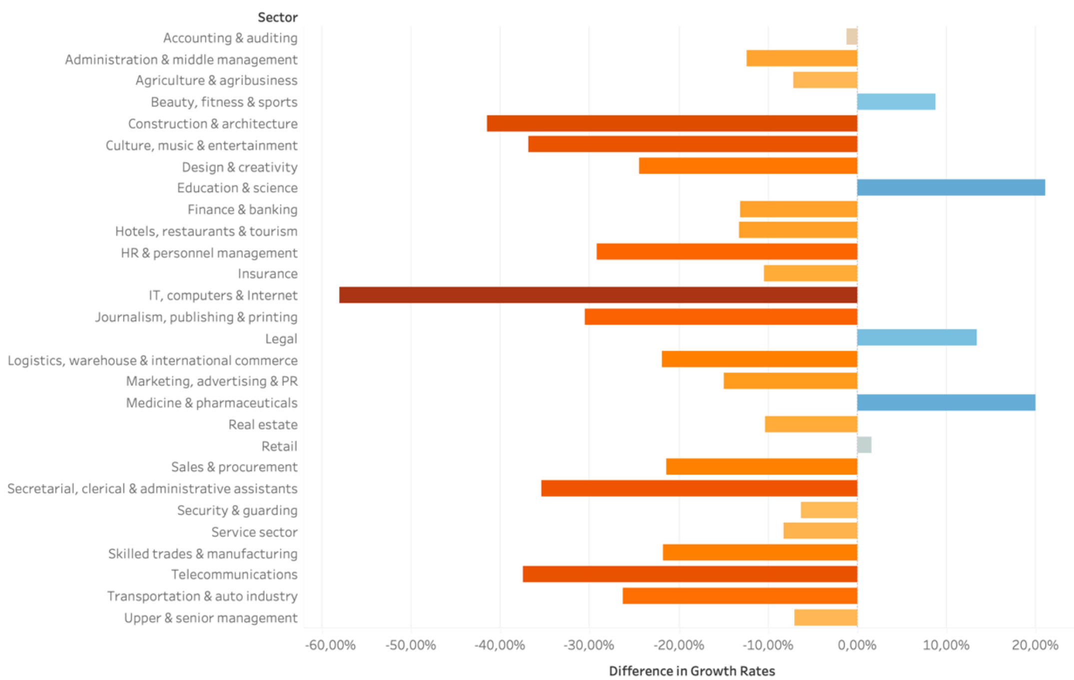
Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)

5.4 Movement inside clusters

In the early beginning of this study, contractions of different economic sectors were discussed. The derived clusters and similarities between occupations could help in efficiently filling the gaps in highly demanded sectors by moving workers from occupations that have a high intersection of skills required.

Figure 8 represents the Difference in Growth rates of Resumes and Vacancies. A bar is in blue if the growth of vacancies is higher than the growth of resumes and is orange if vice versa.

Figure 8. Difference in Growth rates of Resumes and Vacancies (2021-2023)



Source: Work.ua (2021 – 2023)

In the case of the Industrial and Mechanical Trades Cluster, based on Figure 8, the relevant categories on Work.ua (Transportation and Skilled trades categories) demonstrate a lower growth of vacancies compared to the growth of resumes. However, the number of Drivers' resumes grows faster than the number of vacancies, what could be an indicator that demand is not recovering fast enough to employ all job-seekers. Applying similarities from Table 2, Drivers are recommended to switch to Building and Related Trades workers, as they have the highest intersection of skills required and higher growth of vacancies compared to the growth of resumes. Meanwhile, to perform the most efficient transfer of skills, Building, and Related Trades Workers should better choose between Stationary Plant Operators, Metal, Machinery and Related Trades, and Handicraft and Printing Workers.

When switching between occupations, workers should not forget about different occupational barriers. For example, according to Figure 8, there is a high demand for Medicine Workers. An individual from the Health Associate Professionals ISCO group can efficiently transfer their skills to Health Professionals. However, to switch from a nurse to an assistant, an individual should understand the importance of education and experience. However, for business purposes, in case of an urgent need for Health Professionals, it will be less costly to retrain the Health Associate Professionals rather than any other group.

While discussing very differenced clusters, such as the ICT Professionals or Refuse Workers Cluster, workers who are deciding on switching from or to these clusters should account for the skills diversity of these occupations. In the case of Refuse Workers, there is not a big variance of skills demanded, and almost all skills applicable to this group are Transversal Skills. The Transversal Skills definitely could be applied at all clusters, but the other clusters need some occupation-specific skills to be trained.

In the case of ICT technicians, workers should understand that employers from this occupation mostly stress a wide range of technical skills. Also, from the A1 Table, we know that the Business and Administration Professionals group (ISCO 24) is pretty close to the ICT Professional, so they also can perform a good transfer of their skills as their similarity index is 0.89.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

The research question investigated in this study concerns the degree of intersection of skills between different occupations. To discuss the transferability of skills across occupations, clusters of highly similar occupations were created. The analysis in this research is based on vacancies that are web-scrapped from the Work.ua job platform. The date range of web scrapping is from June 2023 to September 2023. Vacancies are taken for all regional centers in Ukraine except the temporarily occupied ones. For Donetsk oblast, Kramatorsk and Slovyansk are taken, as the original center of this oblast at the time of writing this research is under occupation. In total, there are 12995 vacancies recorded and used for this research.

Previous studies of the transferability of skills gave insights that all skills are transferable to some extent. Moreover, the more transferable skills an occupation requires, the more likely individuals will shift from and to such an occupation.

Countries have various factors that predetermine the demand for various skills, and it is important to differentiate countries' specifics. To assess the transferability of skills, foreign researchers mostly use survey-based data, or occupational benchmarks tailored to the other countries' labor market conditions. Because of the lack of surveys and benchmarks for the Ukrainian labor market, the web-scrapping vacancy-based analysis approach is the only option to measure the degree of intersection of skills between occupations. However, analyzing surveys could lead to more precise suggestions on switching between occupations than a web-scrapping approach, as the second one gives only a partial picture of the labor market.

Applying the cosine similarity measure, the similarities between occupations are calculated. However, the vacancy-based approach yields a high average similarity across all occupations, as many vacancies tend to mention similar transversal skill groups across all sectors.

Implications of the results of this study could be captured by individuals, businesses, and government.

To conduct an efficient transfer of skills between occupations, individuals, considering their previous experience and skills can select between the occupations that belong to the same cluster as their previous job. They also should look at the recovered sectors that have enough job places. In the case of moving from or to very distinguished clusters with only one occupation inside, such transfers will require achieving a wider range of skills.

Businesses from recovering sectors that have very dramatic growth can adequately match the demanded skills with the workers' skills by hiring them from the occupations from the cluster of the occupation of interest. Such candidates will not always provide the perfect match of skills, but their retraining will be the least expensive and time-consuming.

The government can focus on the clusters while considering educational programs. While individuals obtain specialized education, the institutions can also focus on the skills demanded by the occupations clustered with the original occupation. For example, students in the Electrical and Electronics Trades program could also get the basics of skills needed for the other occupations from the Industrial and Mechanical Trades Cluster. More advanced skills from this cluster could be obtained at elective courses provided in Electrical and Electronics Trades programs.

Based on the results of this study, there are multiple options for further research on the transferability of skills. The first option is to extend this study to the other sectors that were not captured within Work.ua vacancies. The second option is to conduct an Employer Survey to collect individual data. With the use of gathered information, it will be possible to create relevancy scores in the form of benchmarks needed for replicating Orminston's (2014) study. The first option could give more opportunities for moving inside the existing clusters and extend the skills that could lead to more divorced clusters.

The second option is a shift towards a more precise switching between different occupations.

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APPENDIX

Table A.1. Similarity Matrix

ISCO	12	13	14	21	22	23	24	25	26	31	32	33	34	35	41	42	43	51	52	53	71	72	73	74	81	83	91	93	96
12	1.00	0.97	0.97	0.85	0.77	0.74	0.93	0.78	0.90	0.86	0.81	0.92	0.79	0.86	0.90	0.91	0.82	0.85	0.93	0.86	0.76	0.70	0.73	0.74	0.72	0.72	0.81	0.77	0.60
13	0.97	1.00	0.95	0.90	0.71	0.68	0.93	0.80	0.85	0.90	0.75	0.89	0.75	0.85	0.90	0.85	0.81	0.79	0.86	0.83	0.79	0.74	0.74	0.77	0.75	0.72	0.79	0.78	0.61
14	0.97	0.95	1.00	0.80	0.73	0.72	0.89	0.71	0.85	0.85	0.77	0.91	0.80	0.87	0.86	0.85	0.81	0.83	0.93	0.84	0.76	0.69	0.73	0.74	0.73	0.71	0.81	0.78	0.62
21	0.85	0.90	0.80	1.00	0.69	0.62	0.86	0.84	0.81	0.92	0.72	0.82	0.68	0.75	0.87	0.75	0.78	0.74	0.75	0.78	0.87	0.87	0.81	0.83	0.79	0.75	0.76	0.79	0.59
22	0.77	0.71	0.73	0.69	1.00	0.63	0.70	0.58	0.76	0.74	0.96	0.75	0.70	0.63	0.74	0.73	0.71	0.74	0.74	0.75	0.66	0.63	0.63	0.65	0.66	0.67	0.72	0.70	0.55
23	0.74	0.68	0.72	0.62	0.63	1.00	0.63	0.55	0.82	0.64	0.69	0.67	0.93	0.58	0.64	0.71	0.63	0.72	0.68	0.74	0.58	0.55	0.59	0.60	0.58	0.53	0.64	0.59	0.50
24	0.93	0.93	0.89	0.86	0.70	0.63	1.00	0.89	0.87	0.84	0.74	0.87	0.69	0.86	0.91	0.85	0.79	0.76	0.84	0.81	0.73	0.68	0.69	0.74	0.71	0.68	0.75	0.75	0.57
25	0.78	0.80	0.71	0.84	0.58	0.55	0.89	1.00	0.76	0.76	0.61	0.71	0.58	0.75	0.77	0.73	0.65	0.60	0.67	0.69	0.65	0.65	0.61	0.66	0.63	0.56	0.60	0.62	0.49
26	0.90	0.85	0.85	0.81	0.76	0.82	0.87	0.76	1.00	0.79	0.79	0.84	0.83	0.78	0.84	0.86	0.77	0.80	0.82	0.83	0.72	0.67	0.72	0.75	0.70	0.67	0.75	0.73	0.59
31	0.86	0.90	0.85	0.92	0.74	0.64	0.84	0.76	0.79	1.00	0.80	0.90	0.75	0.79	0.92	0.81	0.89	0.83	0.82	0.88	0.92	0.90	0.89	0.89	0.90	0.86	0.87	0.90	0.73
32	0.81	0.75	0.77	0.72	0.96	0.69	0.74	0.61	0.79	0.80	1.00	0.79	0.75	0.67	0.81	0.81	0.79	0.83	0.79	0.83	0.74	0.70	0.72	0.73	0.75	0.70	0.80	0.78	0.64
33	0.92	0.89	0.91	0.82	0.75	0.67	0.87	0.71	0.84	0.90	0.79	1.00	0.76	0.87	0.92	0.87	0.89	0.87	0.94	0.89	0.84	0.76	0.82	0.82	0.80	0.89	0.89	0.87	0.69
34	0.79	0.75	0.80	0.68	0.70	0.93	0.69	0.58	0.83	0.75	0.75	0.76	1.00	0.73	0.72	0.76	0.73	0.79	0.77	0.86	0.71	0.66	0.70	0.74	0.73	0.66	0.76	0.72	0.70
35	0.86	0.85	0.87	0.75	0.63	0.58	0.86	0.75	0.78	0.79	0.67	0.87	0.73	1.00	0.80	0.85	0.76	0.73	0.88	0.85	0.72	0.64	0.71	0.77	0.74	0.65	0.75	0.73	0.74
41	0.90	0.90	0.86	0.87	0.74	0.64	0.91	0.77	0.84	0.92	0.81	0.92	0.72	0.80	1.00	0.87	0.95	0.88	0.85	0.91	0.88	0.81	0.84	0.86	0.86	0.83	0.91	0.92	0.72
42	0.91	0.85	0.85	0.75	0.73	0.71	0.85	0.73	0.86	0.81	0.81	0.87	0.76	0.85	0.87	1.00	0.81	0.79	0.87	0.88	0.71	0.65	0.70	0.73	0.73	0.67	0.79	0.75	0.70
43	0.82	0.81	0.81	0.78	0.71	0.63	0.79	0.65	0.77	0.89	0.79	0.89	0.73	0.76	0.95	0.81	1.00	0.89	0.80	0.92	0.91	0.82	0.89	0.89	0.92	0.85	0.96	0.98	0.81
51	0.85	0.79	0.83	0.74	0.74	0.72	0.76	0.60	0.80	0.83	0.83	0.87	0.79	0.73	0.88	0.79	0.89	1.00	0.86	0.91	0.84	0.80	0.86	0.87	0.85	0.78	0.95	0.89	0.73
52	0.93	0.86	0.93	0.75	0.74	0.68	0.84	0.67	0.82	0.82	0.79	0.94	0.77	0.88	0.85	0.87	0.80	0.86	1.00	0.84	0.74	0.69	0.73	0.73	0.72	0.73	0.82	0.77	0.62
53	0.86	0.83	0.84	0.78	0.75	0.74	0.81	0.69	0.83	0.88	0.83	0.89	0.86	0.85	0.91	0.88	0.92	0.91	0.84	1.00	0.86	0.78	0.86	0.90	0.90	0.80	0.94	0.91	0.87
71	0.76	0.79	0.76	0.87	0.66	0.58	0.73	0.65	0.72	0.92	0.74	0.84	0.71	0.72	0.88	0.71	0.91	0.84	0.74	0.86	1.00	0.95	0.95	0.94	0.95	0.87	0.91	0.95	0.80
72	0.70	0.74	0.69	0.87	0.63	0.55	0.68	0.65	0.67	0.90	0.70	0.76	0.66	0.64	0.81	0.65	0.82	0.80	0.69	0.78	0.95	1.00	0.91	0.89	0.90	0.79	0.83	0.88	0.70
73	0.73	0.74	0.73	0.81	0.63	0.59	0.69	0.61	0.72	0.89	0.72	0.82	0.70	0.71	0.84	0.70	0.89	0.86	0.73	0.86	0.95	0.91	1.00	0.96	0.95	0.80	0.90	0.94	0.79
74	0.74	0.77	0.74	0.83	0.65	0.60	0.74	0.66	0.75	0.89	0.73	0.82	0.74	0.77	0.86	0.73	0.89	0.87	0.73	0.90	0.94	0.89	0.96	1.00	0.96	0.79	0.91	0.93	0.86
81	0.72	0.75	0.73	0.79	0.66	0.58	0.71	0.63	0.70	0.90	0.75	0.80	0.73	0.74	0.86	0.73	0.92	0.85	0.72	0.90	0.95	0.90	0.95	0.96	1.00	0.81	0.92	0.96	0.89
83	0.72	0.72	0.71	0.75	0.67	0.53	0.68	0.56	0.67	0.86	0.70	0.89	0.66	0.65	0.83	0.67	0.85	0.78	0.73	0.80	0.87	0.79	0.80	0.79	0.81	1.00	0.86	0.86	0.69
91	0.81	0.79	0.81	0.76	0.72	0.64	0.75	0.60	0.75	0.87	0.80	0.89	0.76	0.75	0.91	0.79	0.96	0.95	0.82	0.94	0.91	0.83	0.90	0.91	0.92	0.86	1.00	0.96	0.84
93	0.77	0.78	0.78	0.79	0.70	0.59	0.75	0.62	0.73	0.90	0.78	0.87	0.72	0.73	0.92	0.75	0.98	0.89	0.77	0.91	0.95	0.88	0.94	0.93	0.96	0.86	0.96	1.00	0.83
96	0.60	0.61	0.62	0.59	0.55	0.50	0.57	0.49	0.59	0.73	0.64	0.69	0.70	0.74	0.72	0.70	0.81	0.73	0.62	0.87	0.80	0.70	0.79	0.86	0.89	0.69	0.84	0.83	1.00

Source: Own analysis of Work.ua data (12995 vacancies, June 2023 – September 2023)