

PATHWAYS OF GREENING LABOUR MARKETS: OPPORTUNITIES AND CHALLENGES

Observation in Egypt - Concept Note

Author: Mauro Pelucchi

Reviewers: [Eduarda Castel Branco](#)

Date: 5 February 2023

European Training Foundation

The contents of this draft report are the sole responsibility of the authors and do not necessarily reflect the views of the ETF or the EU institutions.

© European Training Foundation, 2023
Reproduction is authorised, provided the source is acknowledged

CONTENTS

TABLE OF ABBREVIATIONS	4
1. INTRODUCTION	5
2. CONTEXT	7
3. GREEN SKILLS AND GREEN JOBS DEFINITION	9
TERMS SET DEFINITION	12
TERMS EXTRACTION	13
5. ANALYSIS	15
6. ACTIVITIES	19
7. REFERENCES	20

TABLE OF ABBREVIATIONS

API	Application Programming Interface
ESCO	European Skills/Competences, qualifications and Occupations
GDP	Gross domestic product
KDD	Knowledge Discovery in Databases
KPI	Key Performance Indicators
LMI	Labour market information
NEET	Not in employment, education or training
NGO	Non-governmental organisation
OJV	Online Job Vacancy
OJA	Online Job Advertisement
DPS	Data Production System
Q&A	Questions and answers
MB/S	Megabits per second

1. INTRODUCTION

The green economy is a rapidly growing sector globally and has become increasingly important in the context of sustainable development and addressing the challenges of climate change. The concept of green skills refers to the knowledge, competencies, and abilities needed to support the transition to a green economy. The objective of this analysis is to identify the current state of green skills in Egypt and to understand how these skills are being utilised in the country.

The urgency of the climate crisis and demand for sustainability has led most countries around the world to recognize the salience of transition towards “greener” models of production and consumption. This recognition has brought more job availability in the green economy for which appropriate skills (“green” skills) are needed to develop and use green technologies in various sectors.

Therefore, it is more than necessary to understand the extent to which the transition to a green economy induces changes in the demand for skills and which skills these might be. An example of the relevance of this issue is the impact on policy directions: identifying how similar the skill content of green and non-green jobs is can help determine the degree of re-training needed to enable the transition to the green economy (Bowen et al., 2018¹).

The greening of the economies is a potentially disruptive trend for Egypt’s labour markets.

Egypt has made significant strides in the development of its green economy and has recognized the importance of green skills as a critical component of this transition. The country has developed a national strategy for a green economy²³, which aims to promote sustainable economic growth and enhance the competitiveness of its industries.

Together with digital technologies, the twin green & digital transition could be key to achieving the ambitious goal to make Egypt a climate-neutral continent. In addition, going green will play a big role in the recovery after the COVID-19 crisis.

Educators, companies, and policymakers will need to respond to the fundamental changes in industries, occupations, and knowledge required that come with the green revolution. Studies have found that the sizable effects will ripple across many industries and occupations. The current energy price crisis further deepens the need for acceleration of the green transition.

Starting from the online job postings, collected by the ETF system since 2022, we propose a research study to examine the current level of adoption of green skills in the labour market. We will study how requirements for green jobs vary across occupations, industries, and regions. Compared to traditional sources of data, job postings data allows for a detailed, real-time look at the labour market and what employers need. The green skills will be aggregated into the seven pillars of the European Green New

¹Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of ‘greening’ on workforce composition. *Energy Economics*, 72, 263–275.

<https://doi.org/10.1016/j.eneco.2018.03.015>

² https://idsc.gov.eg/Upload/DocumentLibrary/Attachment_A/5903/13-Green%20Economy%20Policies%20and%20Sustainable%20Development%20in%20Egypt.pdf

³ <https://archive.un-page.org/may-egypt-launches-national-strategy-green-economy-amcen>

Deal, which include renewable energy, sustainable transport, sustainable agriculture, sustainable construction, circular economy, digital transformation, and climate-resilient infrastructure.

We will aim to answer the following questions:

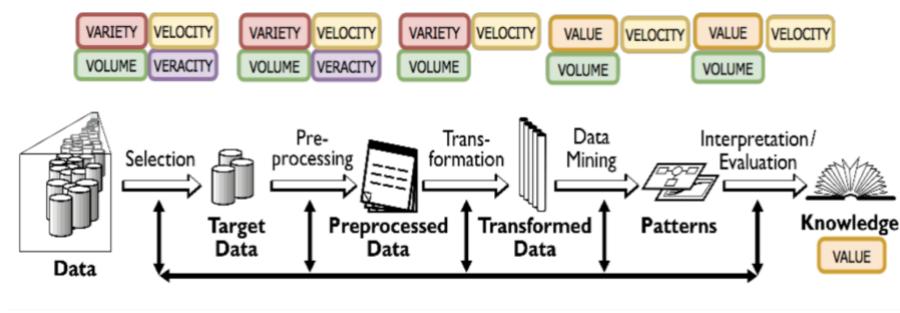
- How does the green skills diffusion differ by industry? What industries rely more on green skills than others? What are the implications of this for economic developers looking to expand local economies and attract new employers? What are the implications for education and workforce development programs that train workers for those industries?
- What are the specific skill requirements in the market today? Within a given occupation, industry, or location, what are the most important skills required by employers? What green skills are most common, most disruptive, and growing fastest?
- How does the adoption of green skills differ across regions? Do some local economies have higher rates of adoption than others? What are the implications of these differences on regional economic development? How do regional differences affect the ability of workers to successfully enter the local economy, and of workers to earn strong wages?
- How do digital skills tie into the greening of the labour market? Which digital skills are most requested in green jobs? Which industries have most successfully adopted the two transitions in tandem? How do green skill requirements relate to requirements for digital skills and result in hybrid jobs – roles that require a unique mix of green and digital skills?

Our analysis will provide insights and implications for green skill development policy as it relates to workforce development and education.

2. CONTEXT

Any analysis that uses Big Data must face several challenges due to the peculiar characteristics of these data sources. Their distinctive features are the variety of data types, the velocity of their production due to the high frequency at which they become available, the large volume of data available for analysis and the need to clearly outline the phenomena that are observed and the risks of manipulation or bias the sources can be subject to, i.e., veracity.

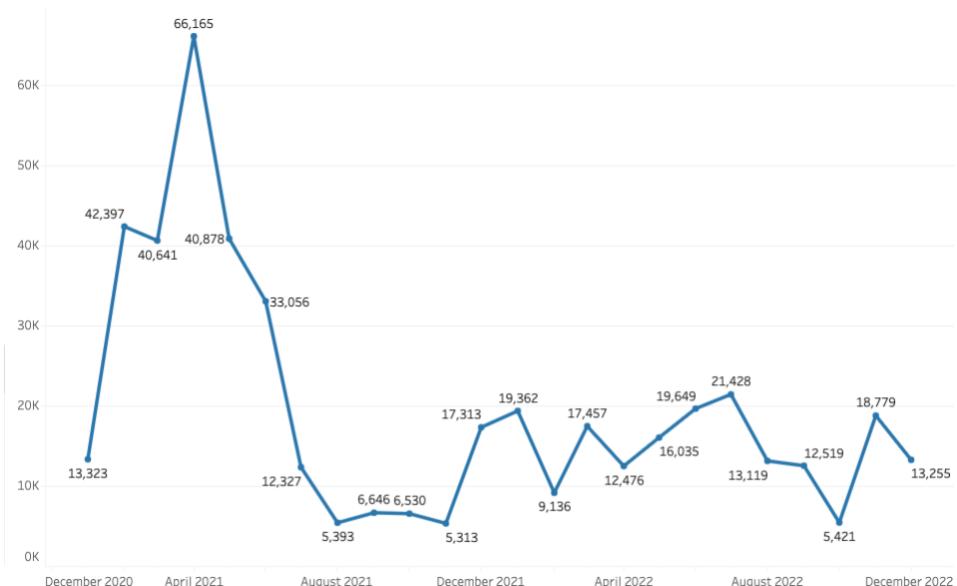
Figure 1 Steps in the knowledge discovery in databases (KDD) approach



The presented analysis can be seen as a vertical pillar applied to the knowledge base built in 2022 and composed by several millions of OJAs collected, cleaned, and classified with respect to the standard taxonomies selected (e.g., ESCO for Occupations and Skills).

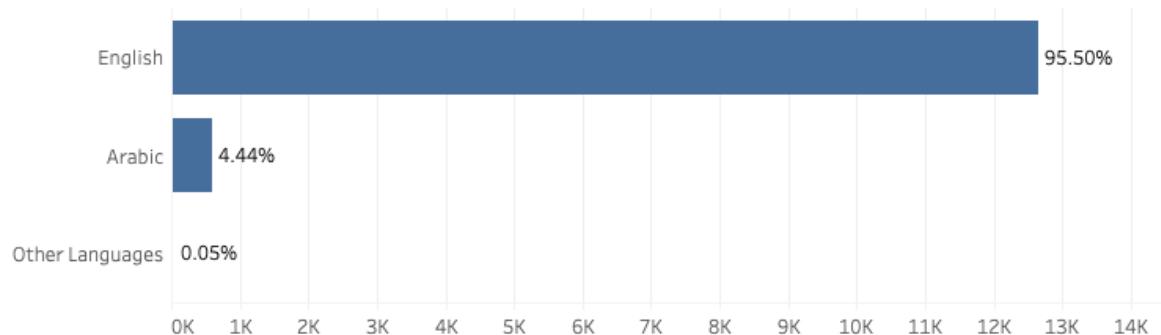
The initiative aims to present one of the possible additional “Angle of Analysis” that can be performed on the knowledge base.

Figure 2 OJAs collected by the ETF system in Egypt



In Egypt the system collected 1,4M job postings since December, 2020. If we consider only the 2022 we observe 734K job postings collected and 178K deduplicated. The system initially processed only the OJAs in English, but starting from October 2022 also the Arabic language.

Figure 3 OJAs English vs Arabic languages (December 2022)



3. GREEN SKILLS AND GREEN JOBS DEFINITION

In order to analyse green skills required by companies in job ads posted online by companies, the taxonomy of ESCO skills applied in previous phases of the project is no longer sufficient. The demand for these skills is in fact a fairly recent innovation in the world of the labour market and they are not yet fully codified in this taxonomy.

The analysis of these competencies must therefore necessarily include, in addition to the technical phase of identification in job ads, a preliminary definitional phase of what competencies are to be sought.

One of the first systemized works on this topic was made by O*NET (Occupational Information Network) for the US context. The Green Economy Program of O*NET, which started around 2009, was designed to collect detailed information (using academic journals, commissioned reports, industry white papers, and governmental technical reports) on green and non-green tasks for around 100 occupations more closely involved in the green economy. Both the green economy and the green tasks that constitute occupations were defined using the output approach that is by the potential to reduce harmful environmental impacts (e.g. by the reduction of the use of fossil fuels, the decreasing pollution and greenhouse gas emission, the developing renewable sources of energy). Using this definition, occupations were classified by experts in three general categories of occupations, that were also included in the O*NET taxonomy: (i) existing occupations that are expected to be in high demand due to the greening of the economy (Green Increased Demand); (ii) occupations that are expected to undergo significant changes in task content due to the greening of the economy (Green-Enhanced Skills); and (iii) new occupations in the green economy (New & Emerging Green).

In the European context, ESCO (European Classification of Occupations, Skills and Competences) has been trying to systemize the current knowledge on this topic and insert the green skills and green occupation in its taxonomy. To do so, ESCO made use of the definition of green skills from 2012 a CEDEFOP: the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment. With this definition, a 3-step based process was constructed to label skills and knowledge concepts as green. The procedure implemented tried to combine human labelling and validation, through the work of a group of experts and the use of Machine Learning (ML) algorithms. ESCO skills were then categorised in three groups: brown skills, which are defined as knowledge and skills that increase the impact of human activity on the environment, white skills, which do not increase nor reduce the impact of human activity on the environment, and green skills, which reduce the impact of human activity on the environment. Using this methodology 571 ESCO skills and knowledge concepts were labelled as green: 381 skills, 185 knowledge concepts, and 5 transversal skills.

As these contributions show, there is a burgeoning literature focused on understanding the green transformation, on identifying what kind of employment opportunities are likely to be created by the transition to a low-carbon economy, and what kind of skills may be in demand, as a result. However, there is still a significant lack of data regarding green skills and green occupations and thus also a lack of data-driven research works.

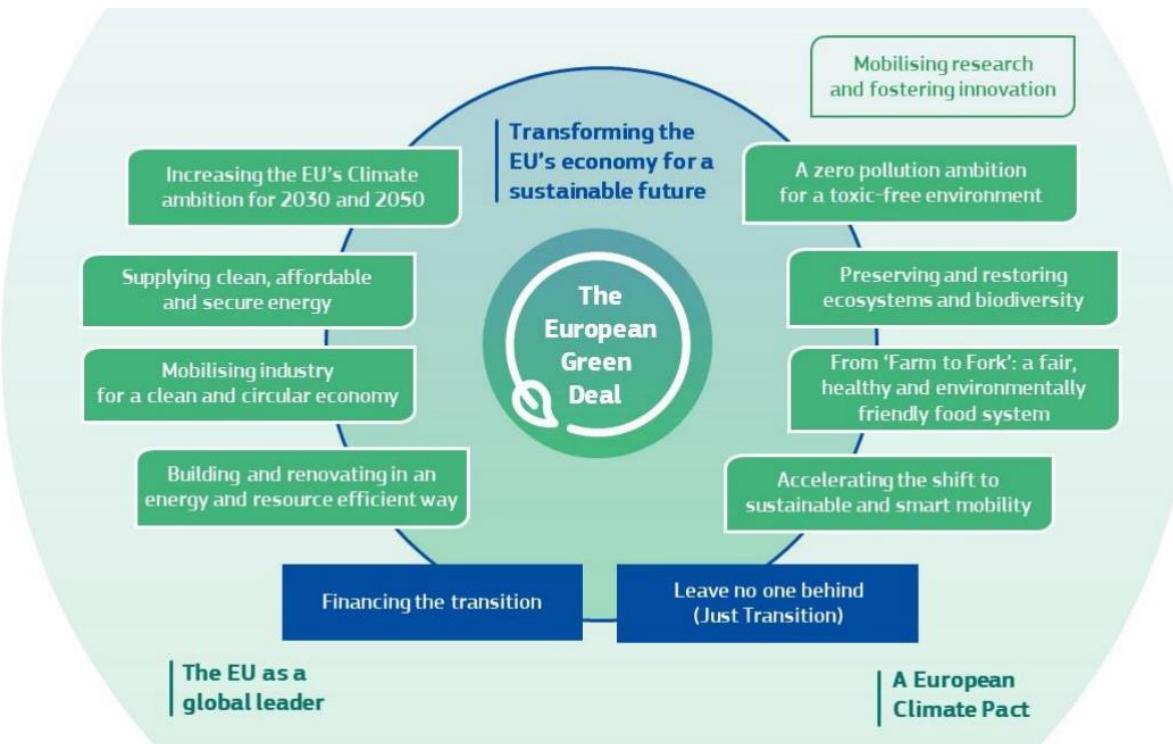
Conceptual box: Data-driven approach

This work is in line with the need for skills and tasks data, since it aims at applying a taxonomy constructed by extracting information from online job ads (i.e., data-driven approach) thus identifying terms related to green as they emerge from the labour

First, we chose to use as a reference framework for the construction of the taxonomy of green skills to be considered the "European Green Deal", the new growth strategy of the European Union presented on Dec 11th, 2019, by the European Commission⁴.

The "European Green Deal" is structured around some specific themes shown in the figure below.

Figure 4 European Green Deal

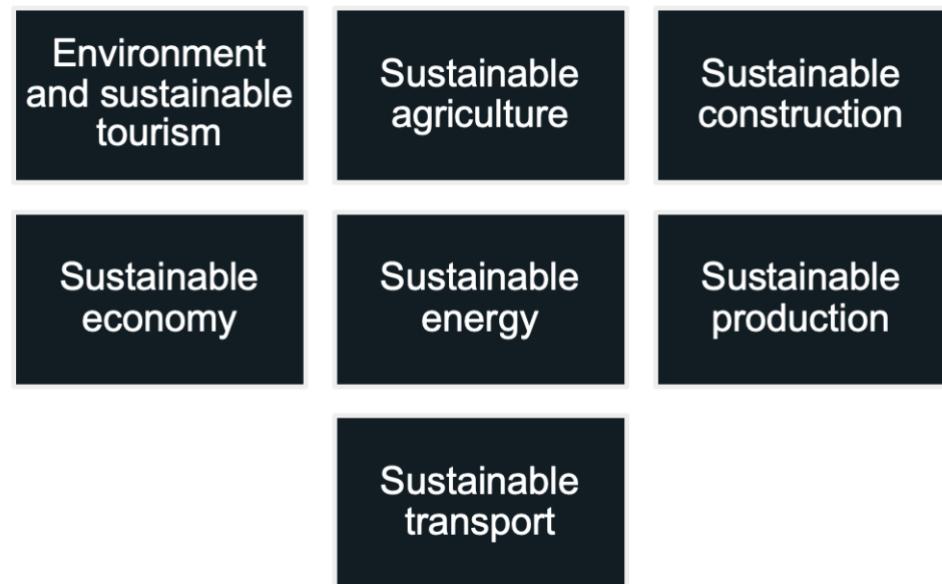


Ensuring coherence with the "policy areas" in which the "European Green Deal" is articulated, seven declinations of green skills have been defined:

- **Environment and sustainable tourism:** the skills related to the management of forests and maritime areas, environmental protection, and management of loss of species and ecosystems as well as their exploitation through sustainable forms of tourism.
- **Sustainable agriculture:** the skills necessary for the development of sustainable agriculture for producers, consumers, and the environment.
- **Sustainable construction:** the skills to initiate a process of renovation and new construction that improves the energy efficiency of buildings and brings building design in line with the circular economy.
- **Sustainable economy:** the skills related to the concept of circular economy.
- **Sustainable energy:** the skills needed to change energy production by replacing current energy sources with renewable energy sources.
- **Sustainable production:** the skills needed to modify current production styles by reducing the environmental impact of companies.
- **Sustainable transport:** the skills related to the reduction of emissions caused by transport both with the use of innovative fuels less polluting and with forms of mobility sharing.

⁴ https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

Figure 5 Policy areas analysed in for the green analysis



4. METHODOLOGY

1. Terms set definition

For each of these areas of expertise, a set of keywords were then defined to be searched for in the job advertisements published online. This phase is critical for the quality of analysis, because the following system, as described below, will use this taxonomy to define which terms have to be identified in the posting corpus and to which green skill declination summarises them.

Due to the relevant impact of this phase, a 2-step approach has been performed:

- 1) First, a set of terms has been selected by domain experts in order to populate the taxonomy. This selection has been based on:
 - a. Already available documents⁵
 - b. Expertise of the person involved in the activity
- 2) Using Language Models (Word embeddings created over the corpus of job postings) the first set of terms is augmented. This step assures that the final terms are data driven.
- 3) Then, this set has been validated and integrated by Country Experts, that provided a review activity focusing on the specific country language and culture

Word embeddings are a type of word representation that allows words with similar meaning to have equal representation. The key idea behind word embeddings is that words with similar frequency distributions tend to have similar meaning. Words are represented by semantic vectors, which are usually induced from a large corpus using co-occurrence statistics or neural network training.

Conceptual box: Main Idea.

The key idea behind word embeddings is that words with similar frequency distributions tend to have similar meanings. In OJAs, the idea is that new emerging skills are more likely to appear together with consolidated ones (ESCO), and this allows us to

Regarding terms set definition, please note that⁶:

- The set does not need to be limited to skills-like terms, but can include general terms that can be found in Postings' text and can be linked to green economy (e.g., Solar power)
- The set of terms is language dependent: each language has its own terms, localised and reflecting specific terminology and culture. So, an extension of this initiative to additional countries/languages will require the translation of the original set and a round of validation by a Country Expert.

Example of green terms:

⁵ SKILLS FOR GREEN JOBS (ILO) https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---ifp_skills/documents/genericdocument/wcms_461268.pdf

Skills for the green transition (ETF) <https://www.etf.europa.eu/en/what-we-do/skills-green-transition-0>

⁶ For this phase only English language will be implemented

Figure 6 Example of green terms by policy area

Construction	Energy	Transport
airtight construction asbestos removal building air tightness building enclosure building envelope building performance energy efficient building Green Architecture green building green building nanocoating green building practice evaluation green building standards green certified construction practices green construction low energy buildings near zero energy building nzeb retrofitting smart thermostat sustainable building sustainable building materials sustainable installation materials thermal insulation zero energy buildings	alternative energy alternative fuels biodiesel biofuels biogas systems biomass biomass systems biorefinery carbon-neutral fuel Carbon negative fuel clean energy cogeneration combined heat and power district heating and cooling efficient energy use energy conservation energy conversion energy efficiency energy efficient operations energy reduction energy saving energy storage energy-from-waste geothermal energy geothermal engineering Geothermal Heat Systems Geothermal Production green energy	alternative fuel vehicles clean fuel clean vehicles bicycle sharing bike sharing carpooling services carsharing Car pooling Car sharing compare alternative vehicles electric drive system electric vehicle Energy Efficient Transportation Flexible fuel vehicles Green Automotive Technologies Green Transportation green vehicle hybrid operating strategies hybrid vehicle Hydrogen vehicle mobility as a service plug-in hybrid powertrain suitability sustainable transport vehicle ecological footprint Hybrid Buses

2. Terms extraction

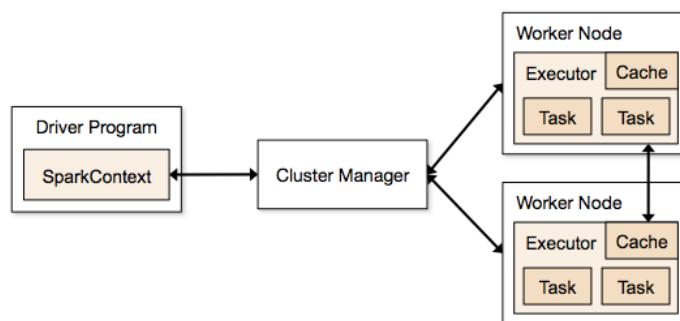
Starting from the set of terms defined above, it's possible to execute a process of information extraction aimed to detect and extract them from postings' text.

In particular, the keyword extraction is a text analysis technique that extracts words and expressions from a text to help to summarise the content of texts and recognize the main topics discussed.

The basic unit of research is often called 'token' which can be a single word or a set of words.

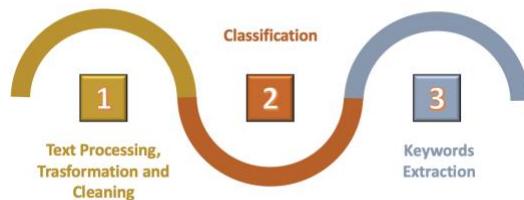
Considering the large amount of data stored in our database, processing job postings requires a highly scalable infrastructure and a distributed framework. For this project we used an Hadoop/Spark approach to analyse and apply machine learning quickly to Big Data. In the state-of-the-art, Spark is an open-source framework used to process large amounts of data, that focuses on processing data in parallel across a cluster.

Figure 7 Hadoop/Spark approach to process large dataset



In order to derive the insights related to the trend of green jobs in the labour market the first step of methodology was to perform text processing to clean and normalise the online job vacancies stored in our databases for EU countries.

Figure 8 NLP based approach for the green analysis



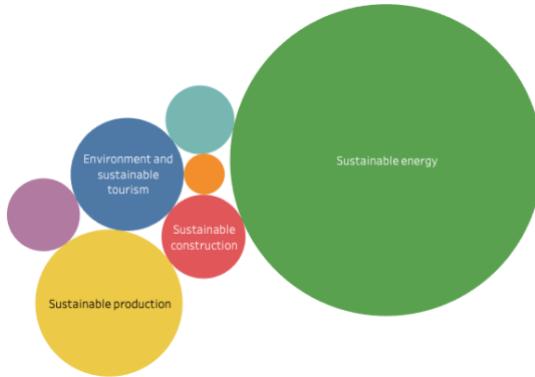
The green data pipelines will be composed by the following steps:

- Pre-processing. Apply state-of-the-art pre-processing functions that include: (i) converting all letters to lowercase; (ii) converting numbers into words or removing numbers; (iii) eliminating punctuations, (iv) accent marks and other diacritics, (v) removing white spaces, (vi) expanding known abbreviations (e.g., aka, asap, etc.), (vii) removing stop words , single digit words, sparse terms, and particular words (viii) text lemmatization and text canonicalization .
- Identify the green OJA. Using a list of sentinel green words – some of them were provided by Cedefop and some were added through a data-driven process we will discuss later – we keep only OJA containing those sentinel green words.
- The filtering is done employing the following regular expression: `fr"\b{clear_word}\b"`
- n-gram generation. This step scans the sentences to identify words that should be considered as a word, for example, “problem” and “solving” are two 1-grams that the pre-processor evaluates as the unified word “problem_solving”. We identified up to 4-grams in the pipeline.
- Skills anchor. To reduce the noise and improve the overall embedding quality, each OJA is converted into a set of texts that are more likely to encode skills. The idea is to use sentinel words as anchors of a window that should only contain the skill-related part of the OJAs to restrict word-embedding processing only to skill sentences to remove the bias. Notably, this step helps in removing green terms related to the description of the company, rather than the job that is expected to be green.

At the end of this step, the set of OJAs can be seen now as a set of “OJA sentences” to be processed by the word-embedding algorithm.

Subsequently, an association between the language of the online job vacancy and the language of the keyword searched was made to build a subset of job advertising that contained only information related to the green job. For a more general level of detail, the keyword identified was also associated with the class to which the skill belonged.

Figure 9 Example of results

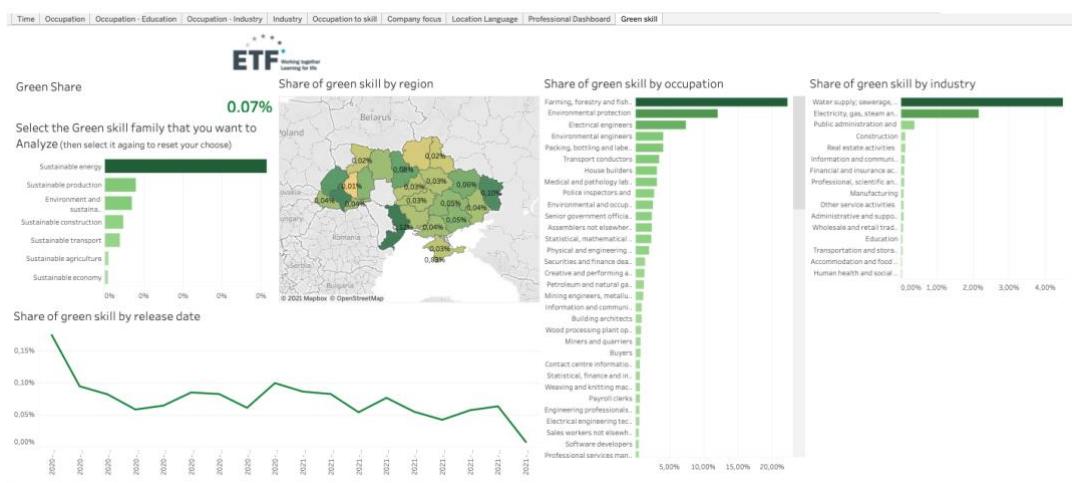


5. ANALYSIS

The data will be delivered with a dashboard. The full dataset will be also available by request.

Here are some examples of insights from the Ukraine use case (ETF).

Figure 10 Ukraine green dashboard (ETF)



In the dashboard we will include different metrics like presented in Table 1.

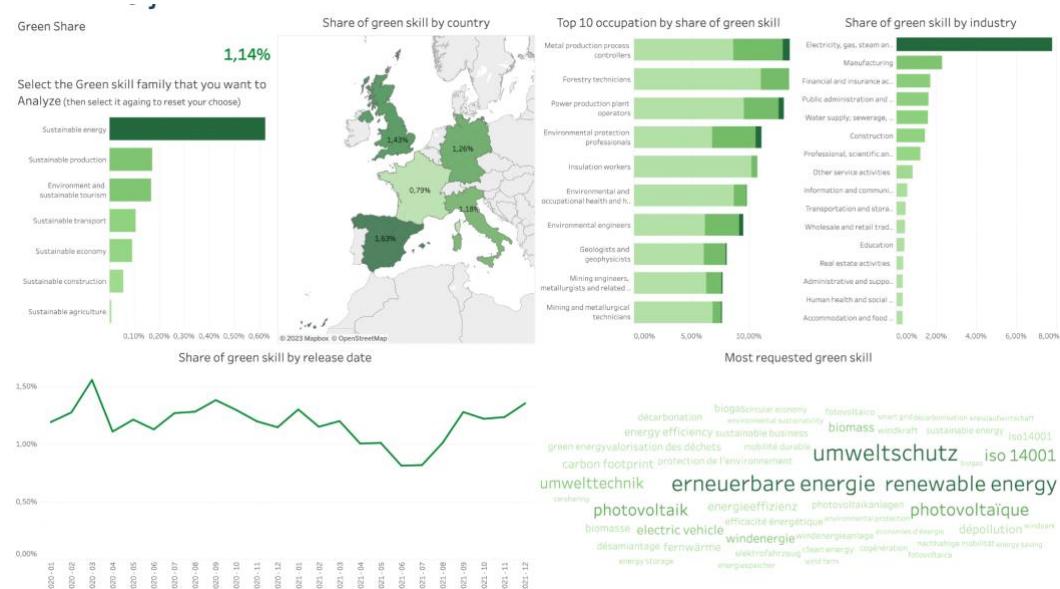
Table 1 - Green metrics

Insight	Description
Green Share	Represents the rate of posting containing at least one term included in the Green Taxonomy
Share of Green Skill by Industry	Represents the most requested NACE Industries associated to postings containing at least one term included in the Green Taxonomy

Share of Green Skill by Occupation	Represents the most requested ESCO Occupations associated to postings containing at least one term included in the Green Taxonomy
Green Intensity	Green intensity is a measure of the distribution of job postings in a particular occupation or industry sector that contain green skills, as extracted from the job description. It is calculated as the distribution of job postings computed by the number of skills extracted from their job description.

In Figure 11, an example of the metrics applied to the EU countries.

Figure 11 Green metrics applied to the EU countries



The dashboards will enable granular analysis:

Figure 11 Green metrics applied to Germany with the reference to the extracted terms.

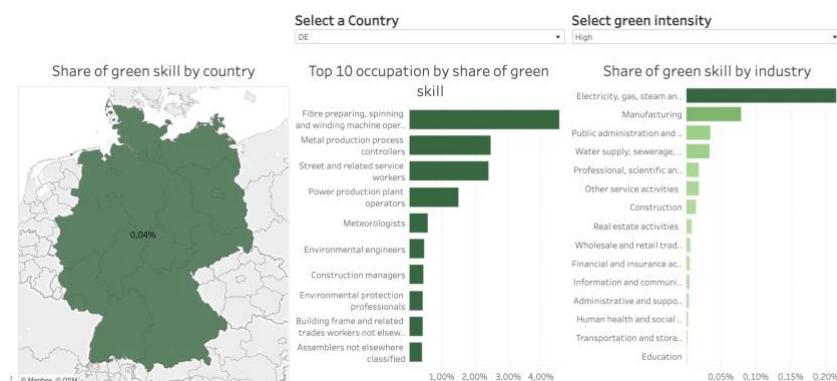
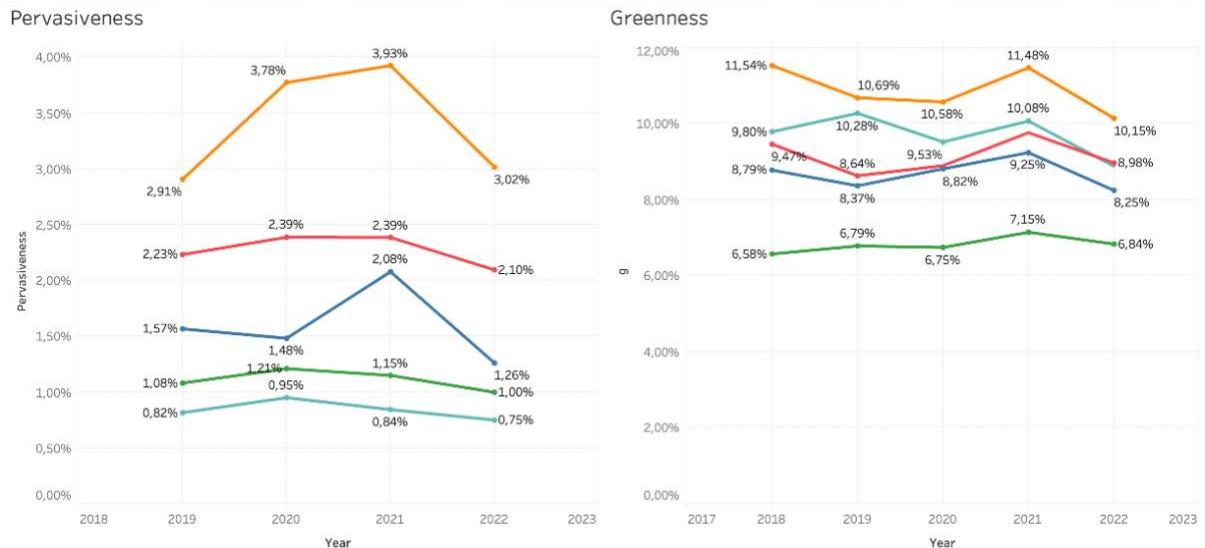


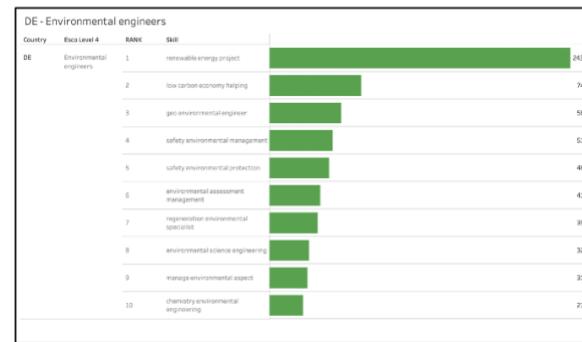
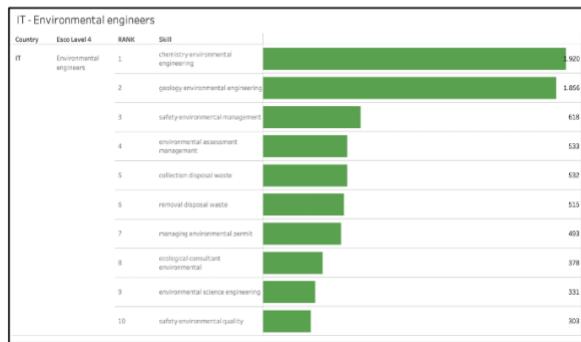
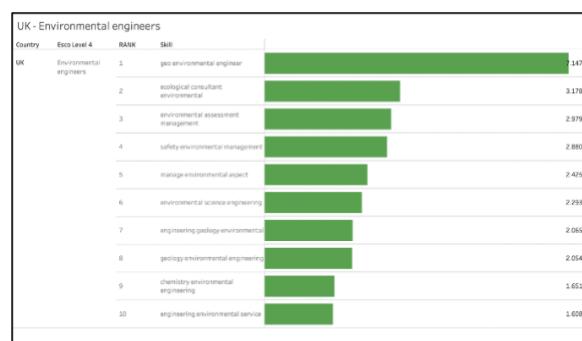
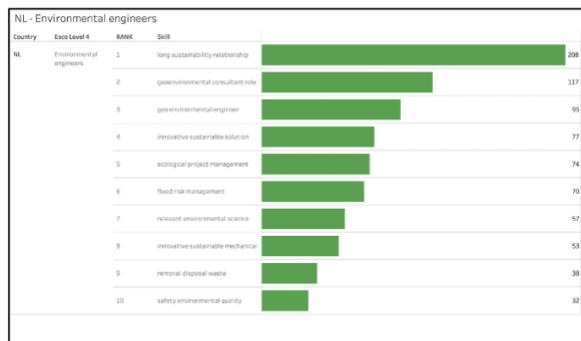


Figure 13 Pervasiveness and Greenness



With the green pillar it is possible to compare occupations across different regions like presented in Figure 14.

Figure 14 Top green skills for Environmental Engineers



6. ACTIVITIES

Type	Task	Completion by
Definition	Determine definition of green jobs	15 February, 2023
Data Prep	Create table with green job postings	20 February, 2023
Analysis	For each region, green shares by industry, location, occupation	28 February, 2023
Analysis	For each region, top skills (technical and human) in green jobs overall	28 February, 2023
Analysis	For each region, top skills (technical and human) in green jobs by industry, location	28 February, 2023
Analysis	For each region, top digital skills in green jobs overall	28 February, 2023
Analysis	For each region, top digital skills in green jobs by industry, location	28 February, 2023
Dashboard	Release the Green Analysis Dashboard	3 March, 2023
Report Writing	1nd draft	
Report Writing	2nd draft and by stakeholders	
Report Writing	Formatting and final release	
Report	Dissemination	June 2023

7. REFERENCES

[1] The twin green & digital transition: How sustainable digital technologies could enable a carbon-neutral EU by 2050 (JRC) - https://joint-research-centre.ec.europa.eu/jrc-news/twin-green-digital-transition-how-sustainable-digital-technologies-could-enable-carbon-neutral-eu-2022-06-29_en

[2] Gatti, Anna Clara, et al. "Understanding Talent Attraction Using Online Job Ads: the Impact of Artificial Intelligence and Green Jobs." *The Relevance of Artificial Intelligence in the Digital and Green Transformation of Regional and Local Labour Markets Across Europe: Perspectives on Employment, Training, Placement, and Social Inclusion* (2022): 129.

[3] European Network of Public Employment Services, Greening of the labour market
<https://op.europa.eu/en/publication-detail/-/publication/a5ce471b-f0dd-11eb-a71c-01aa75ed71a1/language-en>

[4] GREENING THE ECONOMY: EMPLOYMENT AND SKILLS ASPECTS
(https://www.businesseurope.eu/sites/buseur/files/media/reports_and_studies/2021-10-15_employment_and_skills_aspects_of_greening - final.pdf)

[5] Global Green Skills Report 2022 -
<https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/global-green-skills-report/global-green-skills-report-pdf/li-green-economy-report-2022-annex.pdf>

[6] A European Green Deal - https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

[7] SKILLS FOR GREEN JOBS (ILO) https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---ifp_skills/documents/genericdocument/wcms_461268.pdf

[8] Skills for the green transition (ETF) <https://www.etf.europa.eu/en/what-we-do/skills-green-transition-0>

[9] Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, 72, 263–275.
<https://doi.org/10.1016/j.eneco.2018.03.015>

[10] Auktor, G. V. (2021). Green Industrial Skills for a Sustainable Future.
<https://www.semanticscholar.org/paper/Green-Industrial-Skills-for-a-Sustainable-Future-Auktor/0754730859bf5d4e864d511006f3a4dc86fae4b5>

[11] Green Economy Policies and Sustainable Development in Egypt
https://idsc.gov.eg/Upload/DocumentLibrary/Attachment_A/5903/13-Green%20Economy%20Policies%20and%20Sustainable%20Development%20in%20Egypt.pdf