



Big Data Intelligence on Skills Demand and Training in Umbria



Big Data Intelligence on Skills Demand and Training in Umbria

This work is published under the responsibility of the Secretary-General of the OECD. The opinions expressed and arguments employed herein do not necessarily reflect the official views of the Member countries of the OECD.

This document, as well as any data and map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

Please cite this publication as:

OECD (2023), *Big Data Intelligence on Skills Demand and Training in Umbria*, OECD Publishing, Paris,
<https://doi.org/10.1787/4b9bbfd6-en>.

ISBN 978-92-64-51173-6 (print)
ISBN 978-92-64-50970-2 (pdf)
ISBN 978-92-64-79801-4 (HTML)
ISBN 978-92-64-82326-6 (epub)

Photo credits: Cover ©HobbitArt/Shutterstock.com.

Corrigenda to OECD publications may be found on line at: www.oecd.org/about/publishing/corrigenda.htm.

© OECD 2023

The use of this work, whether digital or print, is governed by the Terms and Conditions to be found at <https://www.oecd.org/termsandconditions>.

Foreword

The economic effects of the COVID-19 pandemic have been profound and widespread, prompting the examination of labour and skill needs and their alignment with training opportunities. Umbria, like many regions worldwide, is grappling with the challenges of digitalisation and shifting labour markets.

In response to these challenges, the Organisation for Economic Co-operation and Development (OECD) and the Umbrian regional agency for active labour policies (ARPAL Umbria) have collaborated to examine Umbria's labour market through an innovative lens. Applying big data techniques to online job postings (OJPs), the study aims to understand the changing labour and skill demands of the region, and how well the offerings in the Regional Training Catalogue (RTC) align with these demands.

This study represents a pioneering effort in Italy and Europe, developing new indicators for measuring alignment of RTC course content with labour market demands with the goal to inform policy action for the RTC to better match the rapidly evolving needs of the Umbrian economy.

This work has been carried out by Annikka Lemmens, Filippo Pallucchini, Vito Stefano Bramante and Diego Eslava, under the supervision of Fabio Manca in the OECD Directorate for Employment, Labour and Social Affairs. The report benefitted from comments by colleagues in the OECD, including Stefano Scarpetta (OECD Director for Employment, Labour and Social Affairs) and Glenda Quintini (OECD, Senior Economist, Skills and Employability Division, Directorate for Employment, Labour and Social Affairs). Comments were also kindly provided by Paola Nicastro (Direttore di ARPAL Umbria – Agenzia Regionale per le Politiche Attive del Lavoro), Stefano Sacchi (Professor of Political Science in the Department of Management and Production Engineering at the Polytechnic University of Turin) and Andrea Ricci (Dirigente di Ricerca, INAPP- Istituto Nazionale Analisi delle Politiche Pubbliche). Editorial assistance was provided by Natalie Corry. This report is published with the financial assistance of ARPAL Umbria.

Table of contents

| | |
|--|------------|
| Foreword | 3 |
| Executive summary | 7 |
| 1 Analysis of online job postings in the Umbria region | 9 |
| Tracking the evolution of OJPs in Umbria (and Italy) around the COVID-19 crisis | 12 |
| What occupations and occupational groups capture the largest share of demand channelled through online job postings in Umbria? | 16 |
| The evolution of the demand: Which of Umbria's occupations are on the rise? | 22 |
| What are the job characteristics of fast-growing and emerging occupations? | 29 |
| Demand and supply on the labour market: OJPS versus employment data | 32 |
| References | 37 |
| Annex 1.A. Job characteristics per skill-level | 39 |
| Notes | 47 |
| 2 The Regional Training Catalogue and its supply of training: A descriptive analysis | 49 |
| What kinds of jobs and skills are the focus of the RTC? | 54 |
| The cost and length of the training offer in the Regional Training Catalogue | 63 |
| References | 74 |
| Annex 2.A. Selection of results at the province level | 75 |
| Notes | 78 |
| 3 The alignment between training offered in the Regional Training Catalogue and the labour market | 80 |
| Comparing the occupations in the RTC to OJPs | 82 |
| Comparing the alignment between the demand for skills and the skills taught in the RTC | 91 |
| The skill-match between labour demand and training supply for each occupation | 99 |
| Recent training options: The GOL initiative | 101 |
| References | 104 |
| Annex 3.A. Unique skills across skill-levels | 105 |
| Notes | 106 |
| Annex A. Creating a mapping between the indicators of the demand and supply of skills: Using machine learning to bridge between the RTC and online job postings | 108 |
| Reference | 115 |
| Notes | 115 |

FIGURES

| | |
|--|-----|
| Figure 1.1. Overall trends of OJPs by month in Italy and Umbria | 13 |
| Figure 1.2 Overall trends in Italy and Umbria by skill-level | 15 |
| Figure 1.3. Top 10 Occupational groups at the ISCO-08 2-digit level for Umbria by share of volume of OJPs | 17 |
| Figure 1.4. Top 10 Occupations at the ISCO-08 4-digit level for Umbria by share of OJPs | 20 |
| Figure 1.5. Top 10 fast-growing high-skill occupations at the ISCO-08 4-digit by growth | 24 |
| Figure 1.6. Top 10 fast-growing medium-skill occupations at the ISCO-08 4-digit by growth | 25 |
| Figure 1.7. Trend of fast-growing logistic-related occupations | 27 |
| Figure 1.8. Top 10 fast-growing Low-Skill occupations at the ISCO-08 4-digit by growth | 28 |
| Figure 1.9. Trend of fast-growing food-industry occupations | 29 |
| Figure 1.10. Expected candidate profile – comparison of high-, medium- and low-skilled occupations | 30 |
| Figure 1.11. Offered contract characteristics – comparison of high-, medium- and low-skilled occupations | 31 |
| Figure 1.12. Difference in volume between LFS and OJP at the ISCO-08 2-digit for the years 2018-2021 | 33 |
| Figure 2.1. Example of the Learning Unit of Competence and the Competence Unit | 53 |
| Figure 2.2. Top 40 occupations on which courses in the RTC are focused | 55 |
| Figure 2.3. Number of training courses and intensity per occupational skill level | 56 |
| Figure 2.4. The most prevalent skills taught to participants of the RTC courses | 60 |
| Figure 2.5. Top 30 skills in the terminology of Lightcast, weighted by similarity score | 62 |
| Figure 2.6. Skill clusters weighted by similarity scores | 63 |
| Figure 2.7. Frequencies of cost per training | 64 |
| Figure 2.8. Average cost per training against the average training duration | 64 |
| Figure 2.9. Cost of training courses per occupational skill level | 68 |
| Figure 2.10. Frequencies of training duration | 69 |
| Figure 2.11. Average number of training hours per occupational skill level | 70 |
| Figure 2.12. Frequencies of training duration by occupational skill level | 71 |
| Figure 2.13. Frequencies of the class size per training course | 72 |
| Figure 2.14. Frequencies of costs and duration in the two provinces | 73 |
| Figure 3.1. All occupations for which the demand in OJPs exceeds the training offer | 84 |
| Figure 3.2. Top 20 training courses for occupations which are least demanded and most offered | 86 |
| Figure 3.3. Alignment between share of OJPs and share of RTC training spots | 90 |
| Figure 3.4. Top 20 skills which are most demanded and least offered | 93 |
| Figure 3.5. Skills for which demand in OJPs exceeds the share of RTC training spots | 97 |
| Figure 3.6. Top and bottom 30 occupations by total alignment score | 101 |
| | |
| Annex Figure 1.A.1. Top 10 fast-growing High-Skill occupations – Expected Candidate Profile | 40 |
| Annex Figure 1.A.2. Top 10 fast-growing High-Skill occupations – Offered Contract Characteristics | 41 |
| Annex Figure 1.A.3. Top 10 fast-growing Medium-Skill occupations – Expected Candidate Profile | 42 |
| Annex Figure 1.A.4. Top 10 fast-growing Medium-Skill occupations – Offered Contract Characteristics | 43 |
| Annex Figure 1.A.5. Top 10 fast-growing Low-Skill occupations – Expected Candidate Profile | 45 |
| Annex Figure 1.A.6. Top 10 fast-growing Low-Skill occupations – Offered Contract Characteristics | 46 |
| Annex Figure 2.A.1. The top 30 occupations with the highest number of training hours per occupation in Perugia and Terni | 75 |
| | |
| Figure A A.1. Diagram of the process | 109 |

TABLES

| | |
|--|----|
| Table 1.1. Top 10 fast-growing occupations at the ISCO-08 4-digit level | 22 |
| Table 1.2. Top 10 Occupations at the ISCO 3-digit with highest difference in share between LFS and Lightcast, for the period 2018-2021 | 34 |
| Table 1.3. Tightness indicator for the largest occupations in terms of share of OJPs in 2021 | 36 |
| Table 2.1. Information in the RTC | 51 |
| Table 2.2. Top 10 high-skill occupations with the largest availability of training hours and courses in the RTC | 57 |
| Table 2.3. Top 10 medium-skill occupations with the largest available training offer in the RTC | 58 |
| Table 2.4. Focus for low-skill occupations in the RTC | 59 |

| | |
|---|-----|
| Table 2.5. Example of training courses that take fewer than 20 hours and cost less than EUR 400 | 65 |
| Table 2.6. Example of courses that take more than 200 hours and cost more than EUR 800 | 67 |
| Table 3.1. Occupations that are in high demand but have no training offer in the RTC | 84 |
| Table 3.2. Top 10 occupations without training spots in the RTC, per skill- level | 88 |
| Table 3.3. Top 20 Skills that are in high demand but have no explicit training modules in the RTC | 92 |
| Table 3.4. Top 30 skills which are least demanded and most offered | 94 |
| Table 3.5. Skills that are in high demand that are not offered in the RTC, which are among the top 20 highly demanded skills for multiple skill levels | 96 |
| Table 3.6. Example of the skill-match score calculation | 100 |
| | |
| Annex Table 2.A.1. Top 30 occupations in Perugia, with their training hours, number of training courses and ranking in both regions | 76 |
| Annex Table 3.A.1. Skills that are in high demand that are not offered in the RTC, which are unique in the top 20 highly demanded skills for each skill-level | 105 |
| | |
| Table A A.1. Example of skill extraction | 111 |
| Table A A.2. Example (1/2) of RTC – Lightcast/ESCO most similar match | 113 |
| Table A A.3. Example (2/2) of RTC – Lightcast/ESCO most similar match | 113 |
| Table A A.4. Example (2/2) of RTC – Lightcast/ESCO wrong match replaced with a different skill | 113 |
| Table A A.5. Example (1/2) of RTC – Cluster association | 114 |
| Table A A.6. Example (2/2) of RTC– Cluster association | 114 |

Follow OECD Publications on:



<https://twitter.com/OECD>



<https://www.facebook.com/theOECD>



<https://www.linkedin.com/company/organisation-eco-cooperation-development-organisation-cooperation-developpement-eco/>



<https://www.youtube.com/user/OECDiLibrary>



<https://www.oecd.org/newsletters/>

Executive summary

The COVID-19 pandemic severely impacted the Umbrian economy, and while labour demand has recovered, challenges like digitalisation, tight labour markets, and volatile demand for low-skilled jobs remain.

Against this backdrop, the OECD and the Umbrian regional agency for active labour policies (ARPAL) joined forces to examine the labour and skill demands of the region using innovative big data techniques applied to the analysis of the information collected in online job postings (OJPs). This study also investigates, for the first time in Italy, the alignment between labour and skill demand and the training courses that are available in the Regional Training Catalogue (RTC) managed by ARPAL Umbria and providing information about the educational offerings available in the region.

Results in this study show that labour market demand in Umbria is heterogeneous, with new vacancies being published at all skill levels and that the training options in the RTC are only partly able to align to this varied demand. For instance, as Italian consumers are increasingly turning to online purchases (e-commerce), the logistic sector has experienced significant growth in demand in the region. Although the RTC offers courses for some logistics positions like stock clerks, other highly demanded roles like freight handlers have no specific training options yet. The labour demand for certain food-industry positions, such as waiters, bartenders, and kitchen helpers has also increased, due in part to increased tourism in 2021. While the RTC offers courses for waiters and bartenders, the demand for these workers outpaces the share of training spots in the RTC. In contrast, the RTC focuses heavily on courses for another food industry job: cooks, as 5.2% of all training spots target them, while the number of OJPs is relatively weaker for those professionals.

The RTC also offers many courses for low-skilled occupations such as beauticians and hairdressers, which account for 3.9% and 2.7% of training spots respectively. The labour market demand for these positions – measured by share of OJPs – is much lower than the share of training spots in the RTC. While OJPs may not be able to fully capture the demand for those professionals, the analysis in this report suggests that the current emphasis on these professions in the RTC could be reduced in favour of other occupations showing stronger potential for growth.

Many of the most highly demanded and fastest-growing medium-skill jobs are clerical positions, such as statistical, finance, and insurance clerks; accounting and bookkeeping clerks; secretaries (general); and receptionists (general). The RTC offers many courses for personnel clerks and secretaries but fewer for positions like receptionists or general office clerks. However, it is possible that the skills taught in courses for different types of clerical roles may overlap, making some of the available courses useful to a broad range of clerical jobs.

High-skilled roles, such as business and administration (associate) professionals, are highly present in Umbria's OJPs, partially due to a higher propensity of employers to post these types of vacancies online. The top growing high-skill occupation in Umbria, sales and marketing managers, grew nearly ninefold in terms of OJPs in 2022 with respect to 2018 but targeted courses for managers in that area could be boosted to meet a growing demand.

The RTC has a strong focus on specific digital occupations. The RTC's training courses for ICT user support technicians, advertising and marketing professionals, and web technicians make up 10.7% of the total number of available training spots. As growing demand is expected in those roles due to increased digitalisation, ARPAL should closely monitor the alignment of training content with the fast-changing technological landscape and tailor courses to develop skills that are in high-demand.

Transversal skills such as the ability to adapt to change, work in teams, provide customer service, and problem solving are highly demanded in OJPs but rarely mentioned in the course content of the RTC. Conversely, the RTC focuses disproportionately on health and safety in the workplace and resources could be diverted toward providing training in soft and transversal skills.

This report also builds new and tentative indicators to measure the alignment of the content of the courses to the specific demands of the employers in Umbria in a variety of occupations, by mapping the keywords used to describe the training programmes to those used by employers to describe tasks in jobs. Results suggest that, when training is available, the content aligns relatively well with skill demands in a variety of high and medium skill occupations, but that alignment is weaker across low skilled roles.

In an effort to fill some of the gaps, ARPAL Umbria recently launched new training options within the national programme for the Guarantee of Employability of Workers (GOL). Preliminary evidence seems to suggest that the GOL initiative is providing new learning opportunities in occupations that are in high demand and for which the RTC training offer was relatively weak. Currently, however, the number of training courses implemented in this initiative is still limited (as one could expect due to the short-life of the initiative) and the breadth of the new training options could be extended and better targeted to capture an even more varied range of skills and occupations that are in high demand, following also the indications contained in this report and the priorities highlighted in the results.

Finally, it is important to stress that, while the report provides an innovative view on the labour market, which is key to identify policy priorities, certain high-skilled (technical) professions are often overrepresented in online job postings, while professions that require direct human contact are sometimes underrepresented, calling for caution when interpreting the results and continued monitoring of the potential rapid changes in labour demand triggered by technological change, automation and digitalisation.

1 Analysis of online job postings in the Umbria region

This chapter analyses the demand for labour in Umbria in between January 2018 and June of 2022 as measured by online job postings (OJPs). The analysis examines both long-term trends in demand, caused by factors such as digitalisation and sudden shifts due to the COVID-19 crisis in 2020. The chapter identifies high-demand and rapid-growth occupations and examines their characteristics using information contained in the requirements mentioned in OJPs. In particular, the analysis presents job characteristics such as educational and experiential requirements, as well as the types of contracts offered in job postings. Lastly, the chapter combines online job postings data with employment data obtained from the Labour Force Survey, to compare the prevalence of OJPs with that of employment figures and provide insight into labour shortages.

Highlights

- Umbria's demand for labour as measured by online job postings has generally recovered well after the first peak of the COVID-19 crisis in between January and October of 2020.
- Data on the volume of online job postings (OJPs) also show that a large part of the most highly demanded occupational groups in Umbria are high-skilled roles, such as business and administration (associate) professionals. The top growing high-skill occupation in Umbria, *sales and marketing managers*, grew nearly ninefold in terms of OJPs in 2022 with respect to 2018.
- Many of the most highly demanded and fastest growing medium-skill jobs are clerical positions, some of which require performing advanced administrative tasks, such as statistical, finance, and insurance clerks and accounting and bookkeeping clerks, while others involve completing less sophisticated procedures, such as secretaries (general) and receptionists (general). COVID-19 also had a pronounced impact on the demand for Nursing Professionals which increased almost six-fold during the period examined.
- After the pandemic, certain low-skilled occupations in the food-industry such as waiters, bartenders and kitchen helpers have grown significantly in demand. Similarly, the volume of new job postings for sales roles such as shop sales assistants has increased. The food industry has benefited from increased tourism in Umbria in 2021, while sales roles are most likely in higher demand due to the general economic upturn experienced in 2021 and the start of 2022.
- Information contained in OJPs also indicates that low-skill occupations are more likely than medium-skill and high-skill occupations to receive part-time contracts. They are also slightly less likely to be offered a permanent contract, a factor that can lead to volatility in earnings and uncertainty in working conditions for those workers.
- A comparison between OJPs and data on employment coming from the Italian Labour Force Survey shows that certain high-skilled (technical) professions are often overrepresented in online job postings, while professions that require direct human contact are underrepresented. This calls for caution when interpreting the results. At the same time, the comparison between the rapidly growing volume of new vacancies posted online for certain roles and the figures on employment creation can be helpful to identify areas with emerging labour shortages. This analysis shows that the growth in new OJPs for transport and storage labourers, manufacturing labourers and waiters and bartenders has outpaced the increase in employment in these roles, hinting to potential bottlenecks in those labour market segments.

The region of Umbria in Italy has seen many challenges over the last few years, chief among them the COVID-19 crisis. The labour market has seen important changes due to this unforeseen crisis, but also due to long-term trends such as digitalisation. Trends in online job postings (OJPs)¹ (see also Box 1.1) for the period in between January 2018 – June 2022 highlight an overall positive trend in labour demand for the Umbria region. Despite the heavy burden that the COVID-19 has inflicted on the Italian and Umbrian economy, the number of OJPs has started to increase again, pointing to potential shortages and strong demand.

The labour market in Umbria is relatively tight, but other challenges remain as well. For instance, the demand for workers in low(er) skilled occupations is highly volatile and those workers are also more exposed also to the negative effects of digitalisation, artificial intelligence and automation as well as to higher turnover and seasonal demand in some of these occupations. Such higher volatility means that demand for low-skill occupations is harder to predict and it is hard to know whether certain trends will persist in the future, complicating the planning of effective labour market and training response to these challenges.

Results in this chapter show that, broadly speaking, the labour market demand published online is stronger for high-skilled occupations, than for low-skilled occupations. A relatively strong demand for high-skill workers can pose challenges as both the Umbrian and Italian populations are educated at a relatively lower skill level than other OECD countries (OECD, 2019^[11]). However, data collected on the universe of online job postings published in Umbria also show a significant demand for some low-skilled occupations such as freight-handlers and shop sales assistants.

Box 1.1. Online job postings

This report leverages vacancy data collected from the internet on a monthly basis. This dataset of OJPs spans from January of 2018 to June of 2022 and contains data both at the regional (Umbrian) and national (Italian) level. The data is collected, transformed and harmonised by Lightcast (formerly Emsi-Burning Glass Technologies). The data is composed of 6 762 872 individual level job postings for Italy and 72 434 for Umbria.

The dataset contains up to 70 different variables ranging from skill keywords for each job posting, qualifications and experience required to fill the job, the job's geographical location, as well as the type of contract offered (permanent, temporary). The OECD further transformed the data to create yearly aggregates, cross tabulations and other statistics presented in the document.

Using the information contained in online job postings has two main advantages over traditional data sources such as labour force surveys or national accounting data. Firstly, OJPs make it possible to track trends in a timely manner as OJPs are collected daily from available jobs posted online. Secondly, information in OJPs is more granular than in other data sources, allowing to be much more detailed on the specific occupations and skills that are in high demand across the Umbrian labour market.

OJPs, however, also have some limitations as they may provide less comprehensive coverage of some occupations and sectors where vacancies are not typically advertised through online platforms, which is addressed in a later subsection of this report.

While these data have several advantages when it comes to analyse labour market dynamics (granularity and timeliness), they also have shortcomings and disadvantages that need to be considered. The last section in this chapter addresses potential issues of representativeness by means of a compositional comparison between the EU – Labour Force Survey and the dataset of OJPs used in these analyses. While some high-skill occupations are indeed more featured in the Lightcast data, over- or under-representation does not appear to be a concern for most occupations.

Besides looking at trends in OJPs and detecting the more prominent occupations at different levels of aggregation, this chapter also looks at job characteristics and requirements as they appear in OJPs. In particular, the types of contracts and number of working hours offered to low-skill, medium-skill and high-skill jobs is analysed, as well as the required education level and years of experience.

Tracking the evolution of OJPs in Umbria (and Italy) around the COVID-19 crisis

Umbria's local labour market saw a period of relative growth in the period between 2018 and 2022, in line with the observed national trend. GDP growth in the region for the year 2021 has recorded an impressive 7.1% increase, bringing the GDP per-capita back to pre-COVID levels (Istat, 2022^[2]). The analysis of labour demand, through the lens of Lightcast data, mirrors the positive economic trend,² even after considering the strong decline in economic activity triggered by the COVID-19 pandemic and accompanying lockdowns.

Figure 1.1 shows that the average monthly volume of OJPs for Umbria increased around four times in between January 2018 and June 2022. It should be kept in mind that such an increase is certainly due to an increase in the demand, that is signalling an increase in its tightness, but also to a more widespread use of online channels to advertise new vacancies as digital tools have become more mainstream in the hiring process of Italian firms during the pandemic and in more recent months.

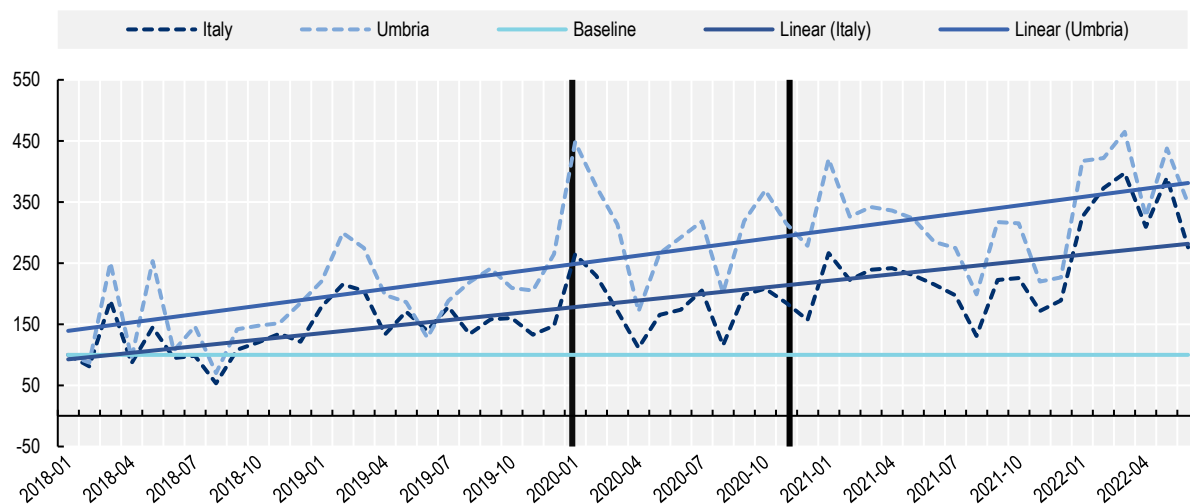
Results also show that the COVID-19 shock strongly influenced the Italian and Umbrian economy during the entire year of 2020. In Figure 1.1 the 'peak of the pandemic period' is enclosed by two vertical lines in between January 2020, when the Italian government declared a "State of Emergency" and the establishment of the so called 'colour system'³ in November of the same year. Within these two dates, a U-shaped pattern characterises the evolution of OJPs.

In Italy, a noticeable decline in new job postings published online can be observed right after the declaration of the emergency state, in between January 2020 and April 2020. The volume of new job postings published in the month of April 2020 dropped to the levels that were recorded approximately two years before the pandemic (in the first semester of 2018), signalling a significant set-back of the labour market demand at the national level. This reduction in labour demand protracted throughout the entirety of 2020, although a mild recovery started in May 2020 when the Italian government declared the end of the first tight lockdown measures and gradually reopened some economic activity.

In the Umbria region the decline in OJPs is even more pronounced than in Italy as a whole. Partially, the pronounced decline can be attributed to the impact of the mobility restrictions during the lockdown on key economic sectors for the Umbrian economy. Right before the pandemic, in 2019, data on employment from the Labour Force Survey indicates that roughly 25% of the labour force was employed in the *Wholesale and retail trade, transport, accommodation and food service activities* sector, roughly 20% in the *Industry sector* and roughly 20% in the *Public administration, defence, education, human health and social work activities*.⁴ All these sectors were severely impacted by the mobility restrictions, which also influenced their labour demand in the form of OJPs.

In January 2020, Umbria experienced a 5-fold increase in the volume of OJPs with respect to January 2018, but during the lockdown the volume of new online job postings published online dropped significantly. The announcement of the colour system in November 2020, with more precise rules to contain the pandemic diffusion and the announcement of a massive vaccination rollout plan in January 2021, led to a moderate restoration of confidence and expectations, providing firms with the possibility to reopen activities and plan new hiring.⁵ This relative return to normalcy is visible one year after the state of emergency was declared, and it signals the beginning of a recovery phase marked by a strong increase in the volume of OJPs starting in January 2021 both in Italy and Umbria. Umbria's recovery has been stronger than in the aggregate figures for the country, in line with a stronger GDP growth in the region relative to the Italian average.

Figure 1.1. Overall trends of OJPs by month in Italy and Umbria



Note: This figure shows the evolution of monthly OJPs relative to the volume of postings in January 2018, normalized to 100, for both Italy and Umbria.

Source: OECD calculations based on Lightcast data.

Evolution in online job postings by required skill levels

Italy's labour market is grappling with skill and qualification mismatches. Only about 1 in 6 adults in Italy holds a tertiary degree, which is among the lowest rates in the OECD countries. This trend is also reflected in the region of Umbria, where a similar figure holds true. (Istat, 2020_[3]). Education figures for Umbria and Italy as a whole are largely comparable, although slightly more Umbrians have obtained a post-secondary school certificate, 34.9% in 2019 compared to 30.9%. Furthermore, skill levels of the Italian adult population are also relatively low compared to other OECD countries (OECD, 2019_[1]). At the same time, in 2016, around 40% of the Italian workforce reported being either over- or under-qualified for their job (OECD, 2019_[1]).

Against this backdrop, the Italian public employment system serves a disproportionately large fraction of job-seekers at the lower end of the skill distribution, individuals for whom caseworkers act as pivotal intermediary in their labour market prospects. To better understand labour demand in this context, it is informative to examine online job postings that are categorized into high, medium, and low-skilled occupational groups,⁶ as in Figure 1.2 (Panel A, B and C).

The evolution of OJPs for high-skilled occupations in Umbria follows closely the Italian trend (see Panel A in Figure 1.2). The two series show a strong correlation (+0.9), indicating that increases (or decreases) in the volume of OJPs in Umbria follow a similar behaviour to the one in the whole Italy, despite a higher overall volatility in Umbria attributable to a relatively lower number of job postings published in the region.⁷

The most notable differences between Umbria and Italy are, instead, observed when comparing the trends in new job postings for medium and low-skilled occupations (Panel B and Panel C, respectively). The growth for these occupations was more pronounced for Umbria than for the Italian benchmark, signalling a relatively higher demand for workers in those occupations at the local level than in Italy. Notably, however, the demand for low skilled workers in Umbria is rather volatile, with OJPs following an irregular pattern of strong and weak demand over time, even within the same year. As further explored in the section when focusing on job characteristics, workers employed in these categories are more likely to face temporary jobs as exemplified by sales workers, sometimes even of a seasonal nature as exemplified, for instance, by workers of the food-industry.

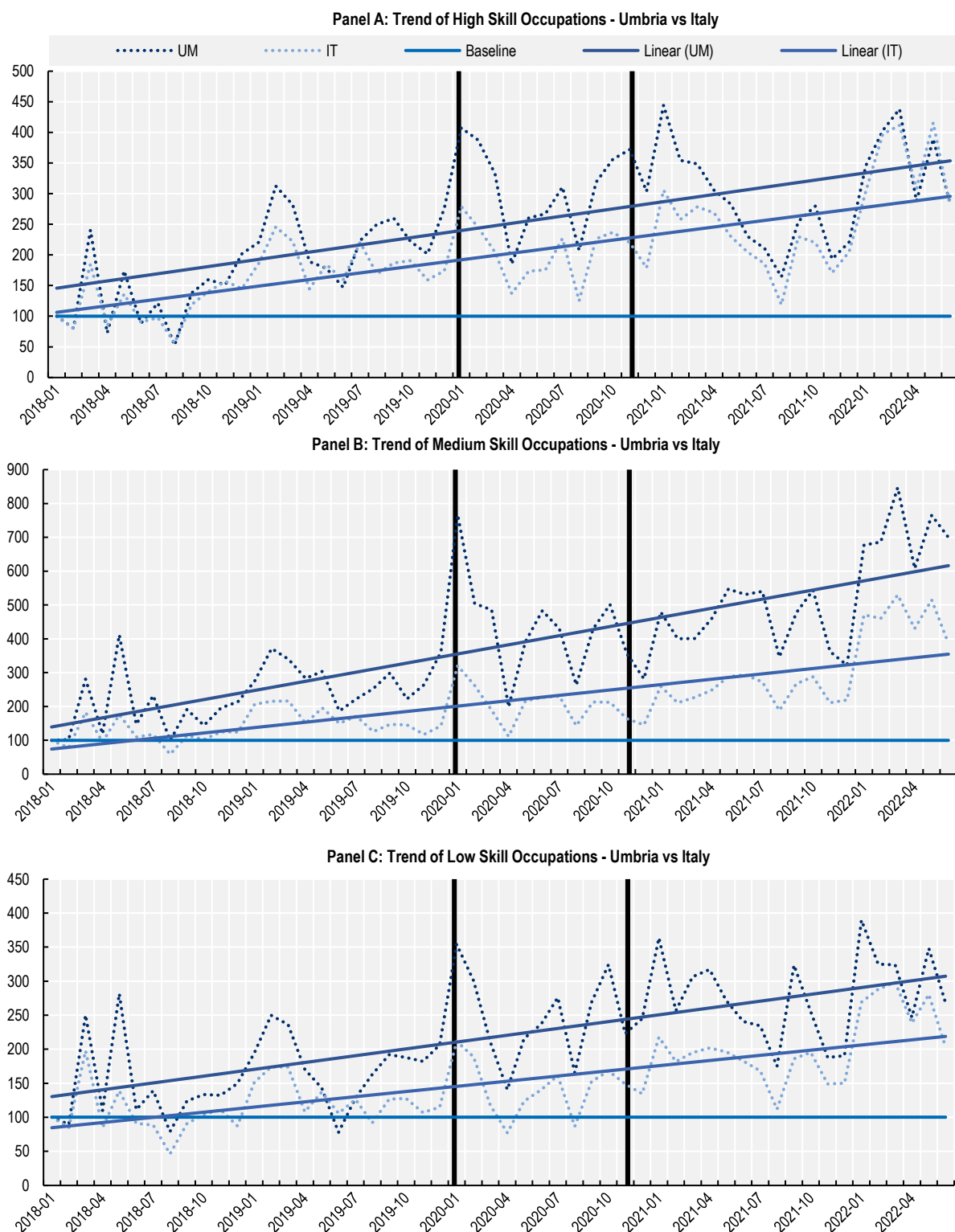
It is worth noting that a very volatile demand for low-skilled workers can represent a challenge when planning and delivering active labour market policies, as low skilled individuals typically represent a large share of the unemployed seeking support from public employment services (PES). For instance, sudden or frequent declines in demand for low-skilled workers, signalled by fewer and more volatile volume of job postings published online over time, can be associated with a rapid increase of benefit claimants, putting particular pressure on PES caseworkers. Similarly, the difficulties in predicting the evolution in the demand for low-skilled workers (due to its high volatility) can limit the ability of the PES to plan the training offered to low-skilled unemployed.

Box 1.2. Public Employment Services and volatile demand

About 42% of all unemployed workers in Italy and 60% in Umbria contact the PES, but at the same time, the PES is facing very high caseloads. On average, in 2016 in Italy, each caseworker was responsible for around 400 unemployed people. While the caseload was lower in Umbria, it still amounted to around 200 cases per PES staff, which is still significantly higher than in most EU countries. Many PES offices also report shortages. In 2016, 83.5% of local employment offices felt that they lacked human resources. In the same year, however, the number of PES staff members was on the decline, worsening the availability of staff. The lack of human resources is among some of the possible reasons as to why fewer Italians contact the PES than in other countries. Individuals may not see the value in contacting the Public Employment Services (PES) due to perceived staffing shortages, which may make it difficult for them to receive assistance. Additionally, there may be concerns about the effectiveness of the PES as a job broker, stemming from their limited resources as well as perceptions about the quality of the services they are able to provide (OECD, 2019^[1]).

PES do not only help unemployed people to find jobs, but they also have a large mandate to help with “upskilling” and “reskilling” (European Commission, 2020^[4]). Upskilling means that people are trained to improve their existing skills, like strengthening people’s existing digital skills. Reskilling on the other hand means that people obtain new skills, for instance, during the pandemic some hospitality workers that lost their jobs retrained to work in health care. The need for upskilling and reskilling is larger for low-skilled workers, who are disproportionately faced with the threat of job automation. Volatile labour demand for low-skilled workers and the accompanying increase in unemployed low-skilled workers can therefore lead to larger demand for skills training. This in turn can increase in caseloads for PES workers, leading to an impact on the quality of service that job seekers receive from the PES.

Figure 1.2 Overall trends in Italy and Umbria by skill-level



Note: Linear trends on panel A, B and C are calculated on a standardised index Jan-2018 = 100. The vertical black dotted lines indicate important COVID-19 related events.

Source: OECD calculations based on Lightcast data.

What occupations and occupational groups capture the largest share of demand channelled through online job postings in Umbria?

The granularity and the high volume of the information contained in OJPs make it possible to obtain insights on trends in the labour market demand at different level of aggregation. In the first part of this section the focus will be on larger occupational groups, using the 2nd digit of the ISCO-08 classification (International Standard Classification of Occupations). This is done to give a broad overview of the labour market demand in Umbria in between January 2018 and June 2022. The second part of this section, instead, focuses on a specific view of the demand for detailed occupations in Umbria, discussing statistics stemming from OJPs at the 4th digit of the ISCO-08 classification. The two analyses are complementary in providing both an overall picture of the aggregate demand and a more nuanced and granular view of the jobs that have been in high demand in Umbria starting from 2018.

A broad view of the labour market demand in Umbria stemming from OJPs

The analysis of the demand in OJPs focusing on large occupational groups shows that a relatively large share of OJPs is concentrated in high skill occupations (ISCO 1 to 3). In fact, 44.7% of all Umbria's OJPs in between January 2018 and June 2022 are aimed at high-skill occupations, compared to 24.5% at medium-skill and 30.8% at low-skill occupations. Statistics on employment at the two-digit ISCO level show 35.4% of all employees work high-skill jobs, 35.7% medium-skill and 28.8% low-skill. This indicates that, at a first approximation, the labour market demand published online is to a large extent seeking high-skilled workers, in higher numbers than are currently employed. Medium-skill jobs are relatively less prominent in the OJPs data than in the employment data. This result can be attributed to a relative strong demand for workers in the high-skill category which could potentially lead to shortages if the demand for these workers is stronger than the labour supply. However, this result can also partially be attributed to the fact that vacancies for those roles are more often posted online than in the case of mid and low skilled workers (discussed in Box 1.3).

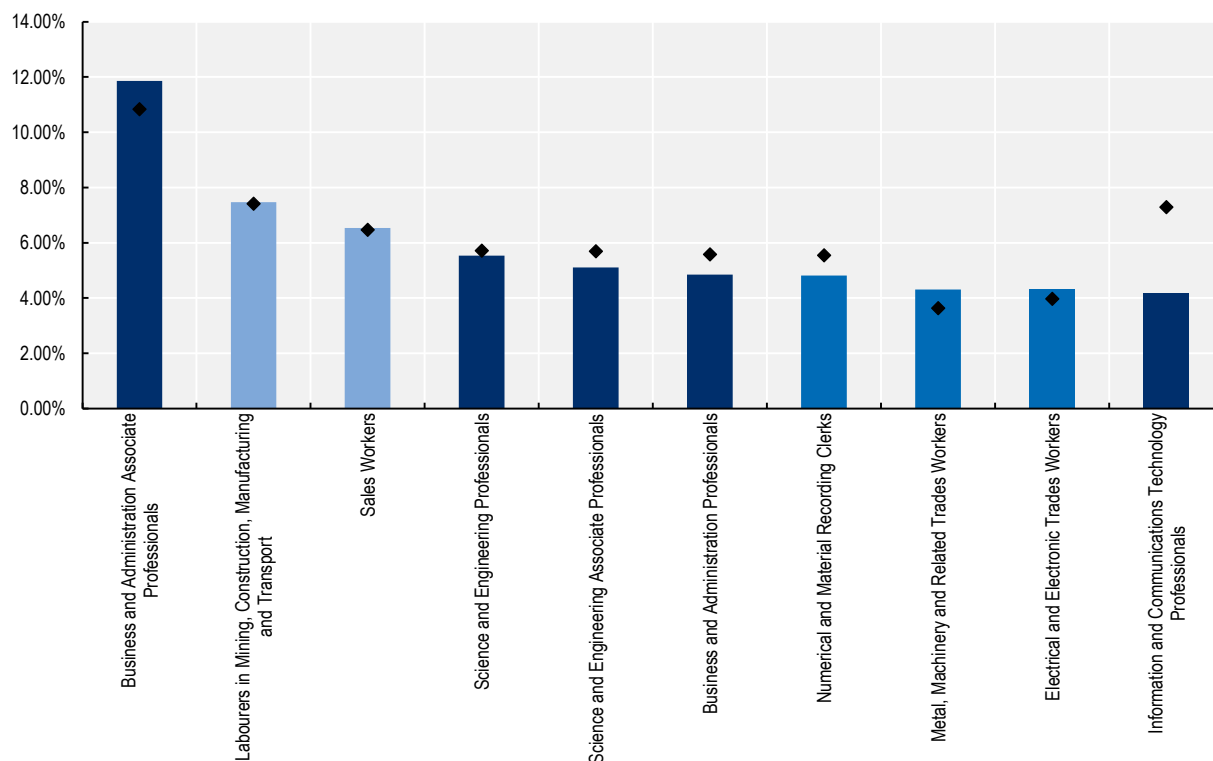
Box 1.3. Prevalence of high skilled jobs in OJPs

A higher prevalence of high-skilled occupations in online job postings is frequently observed. It could mean that there is higher demand for high-skilled workers, but additionally, it has to do with which jobs are more likely to post their vacancies online. For example, (Carnevale, Jayasundera and Repnikov, 2014^[5]) estimate that around 80-90% of postings requiring at least a bachelor's degree can be found online, whereas 40-60% of job postings requiring a high school degree are advertised on the internet. Still, online vacancy data reflect labour demand reasonably well, especially when compared to survey data, and the differences that emerge appear relatively stable over time. (Hershbein and Kahn, 2016^[6]). Moreover, a dedicated subsection assesses how, for Umbria's labour market, the gap between online and offline job posting is closing and it is not cause of concern for the analyses carried out in the remainder of this work.

The analysis in Figure 3 indicates that the demand for the top 10 broad occupational groups (at the 2nd digit level of ISCO) is quite heterogeneous with a higher prevalence of high-skilled occupations within the top 10, followed by relatively more modest demand for workers in medium and low skilled occupations. of all OJPs.

Results in Figure 1.3 reveal that the strength of the demand in Umbria per occupational group as measured by the share of OJPs over the total number OJPs aligns relatively well with the national shares at the broad occupation level. A notable exception is the group of Information and communications technology professionals, which is discussed in the next subsection.

Figure 1.3. Top 10 Occupational groups at the ISCO-08 2-digit level for Umbria by share of volume of OJPs



Note: Each vertical bar represents the share of OJPs for the occupational group at hand relative to the total number of vacancies posted between in Umbria in between January 2018 and June 2022. Dots show the equivalent share of the occupation for the Italian territory. Results are ranked in a decreasing fashion and their colours change depending on whether the occupation belongs to the high (darkest blue), medium (medium blue) or low-skill (lightest blue) class.

Source: OECD calculations based on Lightcast data.

High-skill occupations

Overall, a sizeable share (31.6%) of job postings published in Umbria seeks professionals in five different high-skilled occupational groups (Figure 1.3). Around one third of these OJPs (11.9%) are targeted at Business and Administration-related occupations. In particular, Business and Administration Associate Professionals comprise the largest share of OJPs over the period, and Business and Administration Professionals (4.9%) also make up a significant part of OJPs.

Business and administration professionals perform analytical, conceptual and practical tasks to provide services in financial matters, human resource development, public relations, marketing and sales in the technical, medical, information and communications technology areas. They also conduct reviews of organizational structures, methods and systems as well as quantitative analyses of information affecting investment programmes. Occupations in this sub-major group are Finance Professionals, Administration Professionals or Sales, Marketing and Public Relations Professionals. (ISCO-08, part III).

Business and administration *associate* professionals, instead, perform mostly technical tasks connected with the practical application of knowledge relating to financial accounting and transaction matters, mathematical calculations, human resource development, selling and buying financial instruments, specialized secretarial tasks, and enforcing or applying government rules. Also included are workers who provide business services such as customs clearance, conference planning, job placements, buying and selling real estate or bulk commodities, and serving as agents for performers such as athletes and artists. Examples of occupations in this major occupational group are Financial and Mathematical Associate Professionals, Sales and Purchasing Agents and Brokers or Business Services Agents. (ISCO-08, part III).

All in all, the two occupational groups are similar, but business and administration associate professionals (such as accounting assistants or bookkeeper) tend to carry out tasks of a more technical nature than business and administration professionals (such as financial planners or investment advisers).

Science and engineering-related occupational groups also make up a large share of total online job postings collected in Umbria in the period between 2018 and June 2022. Taken together, Science and Engineering professionals and associate professionals sum to approximately 10.6% of total new job postings published in Umbria.

Science and engineering professionals typically conduct research; improve or develop concepts, theories and operational methods; or apply scientific knowledge relating to fields such as physics, astronomy, meteorology, chemistry, geophysics, geology, biology, ecology, pharmacology, medicine, mathematics, statistics, architecture, engineering, design and technology. Examples of occupations in this group are Physical and Earth Science Professionals or Mathematicians, Actuaries and Statisticians among which there are research-oriented professionals such as Astronomers, Medical or Nuclear physicists. (ISCO-08, part III).

Science and engineering *associate* professionals, instead, perform technical tasks connected with research and operational methods in science and engineering. They supervise and control technical and operational aspects of mining, manufacturing, construction and other engineering operations, and operate technical equipment including aircraft and ships. Specific jobs associated with this occupational group are chemistry, geology or meteorology technicians. (ISCO-08, part III).

The last high-skill occupational group in the top-10 are the Information and communications technology professionals. Approximately 4.2% of the total OJPs over the period of analysis in Umbria were searching for these professionals. This group comprises, amongst others, software and applications developers, database and network professionals, and system analysts. The fact that ICT professionals are among the top-10 occupations suggests an increasing demand for workers with digital skills, driven by the rapid technological progress and the use of ICT that has spread across many different types of workplaces (OECD, 2021^[7]).

The difference in the share of online job postings (OJPs) for ICT professionals is particularly pronounced between Umbria and Italy as a whole. Demand in Umbria (4.2%) lagged behind significantly compared to demand at the national level (7.3%). While the process of digitalisation plays a large role in Umbria's labour market developments, Umbria is likely still in the process of adopting information technology, and less so involved in the *development* of such technology as hinted by the higher requirement of software developers at the national than at the regional level.

Medium-skill occupations

A non-negligible share (13.4%) of the top 10 occupational groups in terms of online job postings seeks medium-skilled professionals belonging to the three very diverse occupational groups. These major occupational categories are *Numerical and material recording clerks*, *Metal, machinery and related trades workers* and *Electrical and electronics trades workers*. Clerks perform much less physically demanding tasks than occupations in the other two groups. All three of these occupational groups, however, do require

education at the second ISCO skill level (ISCO-08, Part III). This entails some form of secondary education. Often, these kinds of jobs require specialised vocational education and/or on-the-job training. Sometimes experience and on-the-job training can be substitutes for formal education. (ISCO-08, part I).

Numerical and material recording clerks help with accounting and bookkeeping records and computations. They also compile statistical, financial and other numerical data. They are often tasked with recording produced, stocked, ordered and dispatched goods, or for example coordinating the timing of passenger and freight transport. Examples of occupations within this group are finance clerks, accounting clerks, wage clerks, and dispatch clerks. (ISCO-08, part III).

Metal, machinery and related trades workers, on the other hand, perform much more physical tasks. They for example use tools and machines to cast, weld, and forge metal. They help install, maintain, and repair heavy metal structures and industrial machinery, including engines and vehicles. Metal casting moulders, welders, lock smiths, machine tool operators, and motorcycle mechanics are all examples of trades within this occupational group. (ISCO-08, part III).

Much like metal, machinery and related trades workers, electrical and electronics trades workers also perform practical tasks. They have to install, fit and maintain electrical wiring systems and machinery. They also inspect and test electrical and electronic systems, equipment, cables, and machinery to identify hazards and defects. Or they for instance join electrical, telecommunications and data cables. Electricians, lift mechanics, electric power line workers, and computer hardware installers for example all fall under the definition of electrical and electronics trades workers. (ISCO-08, part III).

Low-skill occupations

Some 14% of OJPs published in Umbria in the period in between 2018 and 2022, sought workers in low-skilled occupations in the broad occupational groups of *labourers in mining, construction, manufacturing and transport* (7.5%) and *sales workers* (6.7%). These groups are the second and third most sought after employees in terms of OJPs. Their jobs consist of very different types of tasks, with one being manual labour and the other consisting of service jobs. These two ISCO categories make up nearly half of the total number of OJPs looking for low-skilled labour (46%).

Labourers in this occupational group work in different industries but perform similar kinds of tasks. The tasks are routine and involve manual labour. Examples are digging holes and spreading excavated materials, (un)loading, moving, stacking and storing materials, equipment, products, supplies, baggage and cargo, and cleaning machinery, equipment and tools. (ISCO-08, part III).

Sales workers also perform routine tasks, but the labour is not as physically demanding. They sell goods at stores, market stalls, door-to-door or via the telephone. They can also sell and serve food at counters or in the street. Additionally, they can be involved with wrapping or packing the goods, determining the product mix, buying or contracting suppliers for products to be sold, or with determining stock and price levels. Examples of jobs in this occupational group are market vendors, grocers, supermarket supervisors, shop assistants and store cashiers. (ISCO-08, part III).

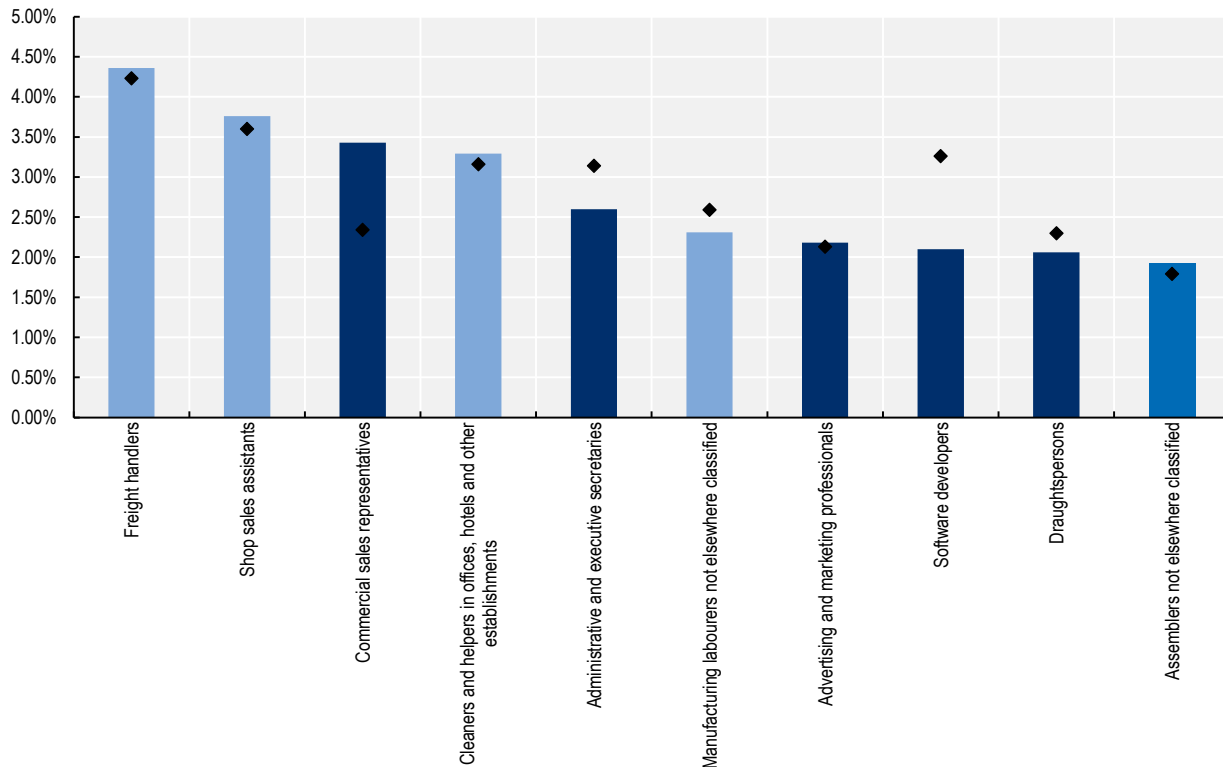
Going granular: What specific occupations recorded the largest shares of job postings in Umbria?

The analysis of broad occupational groups in the previous section gives a sense of the overall dynamics of the demand for workers in Umbria. Using larger occupational groups, however, can mask the more detailed trends at the occupation level. This section therefore looks into the OJPs for a wide range of more detailed occupations, analysing the evolution in the volume of job postings advertised in Umbria for 411 different occupations classified at the 4th digit of the ISCO-08 occupational classification.

Investigating Umbria’s labour market demand at this level of granularity is key to policy makers as it allows to provide more precise indications on what specific occupations may face shortages and labour market bottlenecks. It also enables policy makers to create tailored policies to respond to specific challenges and, for instance, to assess whether the current education and training offer (i.e. the Regional Training Catalogue⁸) matches the particular demands of the local labour market (see Chapter 2).

On the other hand, however, as the analysis focuses on a more granular and detailed set of occupations, the relative availability of information decreases and statistics for smaller occupations may end up being more volatile and, in cases, more difficult to interpret.⁹

Figure 1.4. Top 10 Occupations at the ISCO-08 4-digit level for Umbria by share of OJPs



Note: Each vertical bar represents the share of OJPs for the occupational group at hand relative to the total number of vacancies posted between in Umbria in between January 2018 and June 2022. Dots show the equivalent share of the occupation for the Italian territory. Results are ranked in a decreasing fashion and their colours change depending on whether the occupation belongs to the high (darkest blue), medium (medium blue) or low-skill (lightest blue) class.

Source: OECD calculations based on Lightcast data.

Figure 1.4 presents the average share of OJPs for the top 10 occupations out of the 411 for which information is available at the 4th digit ISCO level. Notably, in between January 2018 and June 2022, the top 10 occupations in Figure 1.4 represent a relatively large share (28%) of total job postings collected for that period.¹⁰

The top 10 occupations in Figure 1.4 range over all skill levels, which confirms the heterogeneous and varied nature of the labour market demand in Umbria. Out of the top ten occupations in Figure 1.4, “assemblers not elsewhere classified” is the only medium-skilled occupation, while there are significantly more low- and high-skilled occupations.

Four out of the top 10 most sought-after occupations at the four-digit level are low-skilled occupations, even though high-skilled occupations were more prevalent in the top 10 at the broader two-digit level. However, looking beyond the top 10, the statistics are unchanged, and 44.7% of all OJPs are for high-skilled labour at this ISCO digit level as well. This result suggests that the demand for high-skilled labour is more spread out over different occupations, while the demand for low-skill labour is much more concentrated in a selected sample of few occupations.

The four low-skill occupations in the top 10 account for 13.8% of all OJPs in Umbria in between Jan-2018 and Jun-2022. Some of these occupations, such as *manufacturing labourers not elsewhere classified and shop sales assistants*, can be seen as the driving reason why the occupational groups *labourers in mining, construction, manufacturing and transport* and *sales workers* were so prevalent when discussing the broader occupational level in the previous subsection.

Freight handlers have the largest share of all OJPs, at 4.4%. They typically “*carry out tasks such as packing, carrying, loading and unloading furniture and other household items, or loading and unloading ship and aircraft cargo and other freight, or carrying and stacking goods in various warehouses*” (see ISCO-08, part III). This is also a job that is highly physical and requires relatively lower qualifications than the average. The increased popularity of e-commerce has had a great impact on the logistics sectors of many countries as well as in Italy. As Italian consumers are increasingly more online, this has led to a significant increase in the number online purchases (e-commerce) which has contributed to the expansion in the demand in the logistic sector.¹¹

The next largest share of online job postings (3.8%) was looking for shop sales assistants. This job is part of the low-skilled occupational group of sales workers, which is one of the high demand occupational groups that was discussed in the previous subsection. Demand for sales workers contributed to 6.5% of all OJPs, and more than half of those OJPs are specifically looking for shop sales assistants. A shop sales assistant’s tasks are: “*selling a range of goods and services directly to the public or on behalf of retail and wholesale establishments, and explain the functions and qualities of these goods and services.*” (ISCO-08, part III).

Commercial sales representative is another sales-related job that is part of the top 10 jobs with the largest shares of OJPs in Umbria. These workers, among which after-sales service adviser, canvassers or commercial travellers, typically “*represent companies to sell various goods and services to businesses and other organizations and provide product specific information as required*”. They usually solicit orders and sell goods to retail, industrial, wholesale and other establishments. Among their tasks, commercial sales representatives also obtain and update knowledge of market conditions and of employer’s and competitors’ goods and services selling equipment, supplies and related services to business establishments or individuals. This is a high-skilled job that is part of the highly demanded broader occupational group of business and administration associate professionals.

When comparing the number of average job postings in Umbria and Italy, the most notable difference is found for the occupation of *software developers* (Figure 1.4). This occupation represents a smaller share of the overall demand in Umbria (2% share of total OJPs) relative to Italy as a whole (3.1%). This is in accordance with what was observed in Figure 1.3, where the demand for ICT professionals is significantly higher in Italy as a whole than in Umbria specifically. Again, it could be because Umbria’s enterprises are more focused on adopting the existing information technology in the process of digitalisation, and are less involved in the aspects related to its *development*.

While the analysis of the list of top 10 occupations offers a perspective on those jobs making up the largest volume of vacancies in Umbria, it does not allow to appreciate the dynamics in the demand, and hence, how, if at all, trends are changing over time. The next section will discuss the evolution of the demand and the potential shift that may have happened over time in Umbria with the aim of highlighting where and how much the demand has shifted.

The evolution of the demand: Which of Umbria's occupations are on the rise?

Mega trends such as digitalisation and population ageing, or even sudden and unprecedented shocks such as the COVID-19 pandemic, are reshaping labour markets and skill demands radically. To capture these changes, this section focuses on the evolution of the demand for labour by identifying and analysing occupations for which the number of online job postings has increased most notably in Umbria. Focussing on the dynamics (the *growth*) rather than on a static picture of the demand makes it possible to isolate occupations that have the potential to *change* the composition of the labour market. Whether that potential will translate into employment depends on how the supply side of the market, the workforce, responds to the new and emerging need of the demand side. In this ever-evolving environment the PES can act as an informed intermediary, aligning the expectations of both sides of the market.

The *fast-growing* occupations differ from the top 10 occupations presented in section 1 (as can be seen in Figure 1.4 and Table 1.1). This shows that demand patterns in the labour market are changing. The table should be read as follows: *Advertising and marketing professionals*, the last entry in Table 1.1, have grown from a (very low) average of approximately 7 new job postings published online per month in the first semester of 2018 (column (1) to an average of 41 new online postings per month in the first semester of 2022 (column (2)). The volume of job postings for this occupation has, hence, increased roughly 6 times (growth factor) in the period under consideration, signalling increasing demand for professionals in that occupation. Details about the calculation of growth factors can be found in Box 1.4. While the current demand for the fast-growing occupations may seem low in absolute terms, the analysis of the dynamics for these occupations can shed light on interesting and emerging patterns in the labour market.

Table 1.1. Top 10 fast-growing occupations at the ISCO-08 4-digit level

| Occupational code (ISCO-08) | Occupation title | Average OJPs per month (January-June 2018) (1) | Average OJPs per month (January-June 2022) (2) | Growth factor (2)/(1) |
|-----------------------------|---|---|---|-----------------------|
| 2359 | Teaching professionals not elsewhere classified* | 0.17 | 8.00 | 48.00 |
| 3423 | Fitness and recreation instructors and program leaders* | 1.33 | 14.17 | 10.62 |
| 3315 | Valuers and loss assessors* | 1.17 | 12.00 | 10.29 |
| 4110 | General office clerks* | 1.67 | 16.00 | 9.60 |
| 4419 | Clerical support workers not elsewhere classified | 2.50 | 21.83 | 8.73 |
| 1221 | Sales and marketing managers | 2.67 | 23.17 | 8.69 |
| 5131 | Waiters | 7.33 | 47.67 | 6.50 |
| 5244 | Contact centre salespersons | 2.50 | 15.83 | 6.33 |
| 2221 | Nursing professionals | 2.00 | 11.67 | 5.83 |
| 2431 | Advertising and marketing professionals | 7.33 | 41.50 | 5.66 |

Note: Column (1) contains the average number of OJPs in the first semester of 2018; column "S1-22 (Avg)" contains the average number of OJPs posted in the first semester of 2022. Column "Growth" contains the ratio of the values reported in S1-22 (Avg) over the values reported in S1-18 (Avg). The occupations displayed have an average number of OJPs above the overall mean of 7.92 OJPs per month throughout the period. * Denote occupations with emerging demand.

Source: OECD calculations based on Lightcast data.

Box 1.4. Calculation of fastest-growing occupations and occupations with emerging demand

Trends in demand are measured by computing the growth factor (i.e. the ratio) between the average number of new monthly OJPs in the first semester of 2022 relative to those published in the first semester of 2018 in each occupation. Only occupations that have an average number of monthly OJPs larger than the mean for the entire period (7.92 OJPs) are included in the analysis, and the top ten *fastest-growing* occupations per skill level are discussed. Using a growth factor calculated as the ratio between OJPs in two periods of time has the advantage of being simple to interpret. Moreover, by comparing the same months of two different years makes it possible to control for the seasonality patterns that might affect an occupation and confound a measure of growth.

Yet, the growth factor is sensitive to the starting average number job postings in the first semester of 2018; as it is the denominator. If the starting number of OJPs was very low, this number can inflate the growth. When this is the case, this limitation is pointed out to inform the reader to be cautious in the interpretation of the growth factor. At the same time, these jobs are interesting as these occupations can represent new and *emerging demand* across Umbria's online labour market. These occupations are included to showcase their exceptional growth, despite small starting numbers and are treated separately in the next subsection. Occupations with emerging demand had a below average number of monthly OJPs in the first semester of 2018 (1.87) compared to all occupations but had more than 7.92 average monthly OJPs over the entire time period.

Source: OECD calculations based on Lightcast data.

Occupations with emerging demand

The top four fastest-growing occupations in Umbria when comparing the first semester of 2022 to the first semester of 2018 can all be considered occupations with emerging demand (See Box 1.4). While caution is necessary when looking at the absolute values of their growth factors, as they had a very low average number of OJPs in the first semester of 2018, these occupations are still characterised by exceptionally large growth. Three out of these four occupations are high-skill: *Teaching professionals not elsewhere classified*, *Fitness and recreation instructors and program leaders*, and *Valuers and loss assessors*, while the last one: *General office clerks*,¹² requires medium-skill.

The average number of OJPs grew most rapidly for *Teaching professionals not elsewhere classified*, as it increased around 48 times during the period of analysis. This occupation includes those who provide educational counselling to students. The COVID-19 crisis has shown the limits of remotely provided education (DaD, Didattica a Distanza), leading many parents and students to seek out privately held counselling to boost students' performance, which increased demand for this occupational group starting in 2020. After the peak of the pandemic passed, demand remains still high.

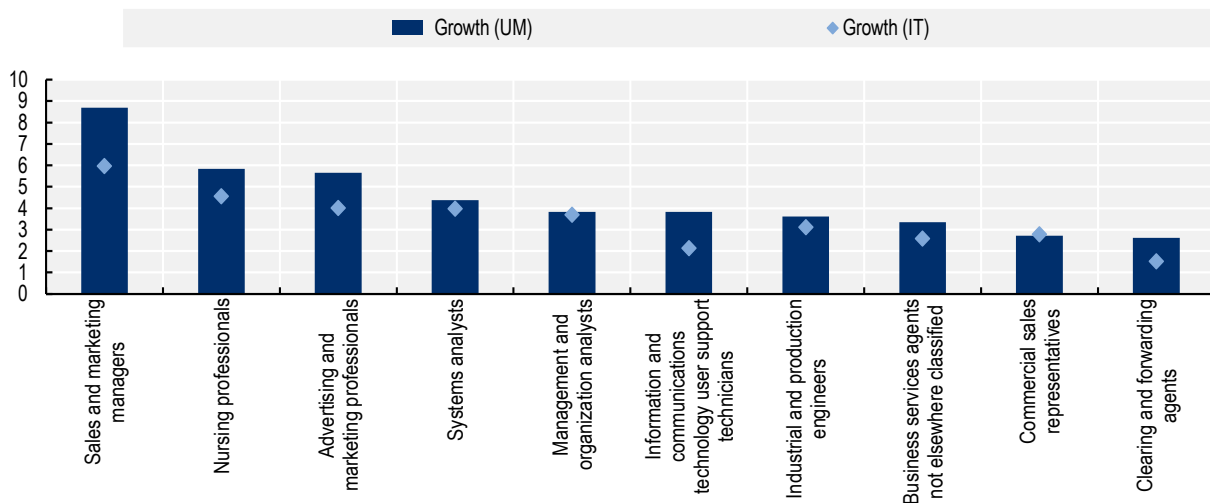
The number of OJPs for *Fitness and recreation instructors and program leaders* increased from 1.3 up to 14.2 on average per month. Aerobics instructors, fitness instructors, personal trainers, and even jobs like sailing instructor and horse-riding instructor are all examples of this occupation. The exceptional growth in OJPs can be evidence that this job is currently more advertised online than it was previously, or perhaps the pandemic brought extra awareness of the importance of physical activity for general health. Studies have for example shown the benefits of home-based exercise and of a physically active lifestyle during the pandemic (Ravalli and Musumeci, 2020^[8]; Pippi and Fanelli, 2021^[9]).

Valuers and loss assessors are employees that value property and various goods, and assess losses covered by insurance policies. OJPs for this job increased over tenfold in between 2018 and 2022, meaning that this job is now the 47th most in demand job out of 411. In 2018 it was ranked 109th. Potentially, this is due to a post-COVID increase in bankruptcies in Umbria in 2021 and 2022 (INSOL Europe, 2021^[10]; INSOL Europe, 2022^[11]), which require assessment by insurers. Unlike Italy as a whole, the Umbria region saw increased bankruptcies in 2021 and 2022.

High-skill occupations with increasing demand in online job postings

The ten fastest growing high-skilled occupations in Umbria grew in between 8.7 and 2.6 times (Figure 1.5). The fastest growing occupation was a managerial job: Sales and marketing managers. The slowest growing occupation in the top ten, *Clearing and forwarding agents*, still grew nearly threefold. The former is the only managerial function in the top 10, with five of the remaining nine occupations being roles as “professionals”, and four occupations which are “technicians and associate professionals”.

Figure 1.5. Top 10 fast-growing high-skill occupations at the ISCO-08 4-digit by growth



Note: Bars represent the growth for each occupation expressed as a simple ratio between the average number of OJPs in the first semester of 2022 over the average number of OJPs posted in the first semester of 2018. Dots overlaying each bar show the equivalent growth of the same occupation for the Italian territory. The occupations displayed have an average number of OJPs above the overall mean of 7.92 OJPs per month. Four occupations with emerging demand have been excluded from the graph: Teaching professionals not elsewhere classified, Fitness and recreation instructors and program leaders, Valuers and loss assessors, and Research and development managers.

Source: OECD calculations based on Lightcast data.

COVID-19 had a pronounced positive impact on the demand for certain high-skilled occupations. In particular the number of OJPs for *Nursing Professionals*, increased almost six-fold during the period. The COVID-19 crisis was first and foremost a health crisis, leading to increased rates of hospitalisations in both Umbria and Italy as a whole. This increased pressure and work-related stress for health care professionals (Paolucci et al., 2021^[12]). Furthermore, the Italian health care system was already dealing with an aging workforce and with budget cuts, worsening the ease with which new staff could be found (Gostoli, 2020^[13]).

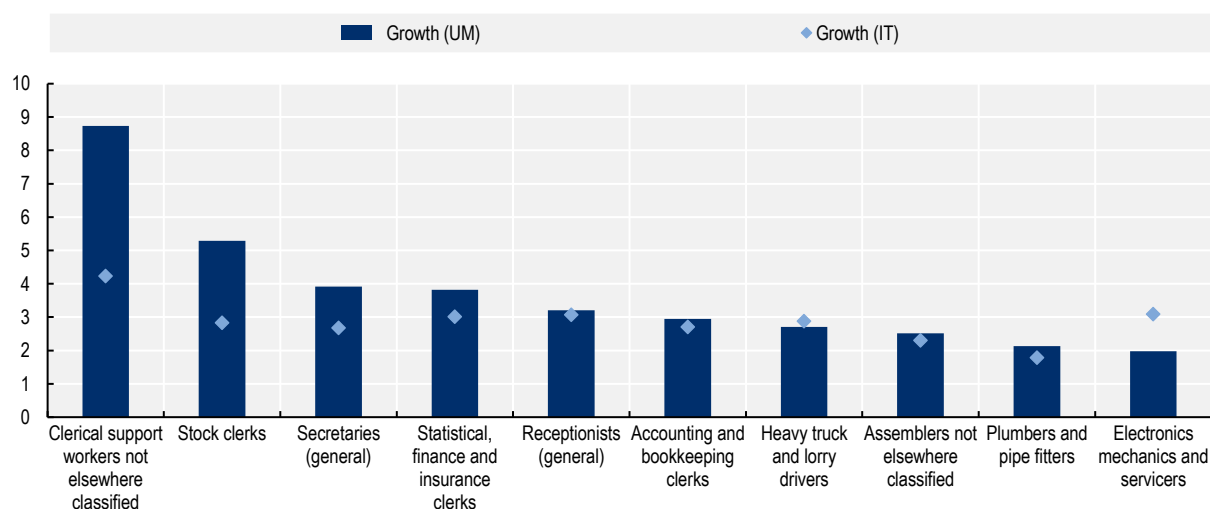
The other “professional” roles in the top ten represent occupations that are typically performed in a business setting within companies: advertising and marketing professionals, systems analysts, management and organisation analysts and industrial and production engineers. Demand for advertising and marketing professionals increased fivefold over the period, followed by system analysts which increased around 4.4 times. The number of OJPs for management and organization analysts increased nearly fourfold, and OJPs for industrial and production engineers around threefold. These occupations encompass four different areas that are typically associated with the operations of a company: sales, information technology, management, and product design.

Among the associate professionals, the demand for information technology user support is particularly high. IT roles are in demand in multiple different sectors, making the gap between demand and supply difficult to fill. This is reflected in sectoral studies (Umbria Domani, 2022^[14]) and agreements between technical schools and the chamber of commerce (Perugia Today, 2022^[15]), which are encouraging young high-school graduates to pursue IT positions.

Medium-skill occupations with increasing demand in online job postings

Concerning the medium skill occupations, most of the fastest-growing occupations are subgroups of *Clerical Support Workers*, as can be seen from Figure 1.6. These business-related jobs cover six out of the ten entries. Clerks are endowed with tasks such as recording, organising or retrieving information related to the functioning of a firm and can be seen as complementary to the fast-rising high-skill business-related jobs mentioned in the previous paragraph.

Figure 1.6. Top 10 fast-growing medium-skill occupations at the ISCO-08 4-digit by growth



Note: Bars represent the growth for each occupation expressed as a simple ratio between the average number of OJPs in the first semester of 2022 over the average number of OJPs posted in the first semester of 2018. Dots overlaying each bar show the equivalent growth of the same occupation for the Italian territory. The occupations displayed have an average number of OJPs above the overall mean of 7.92 OJPs per month. One occupation with emerging demand has been excluded from the graph: General office clerks.

Source: OECD calculations based on Lightcast data.

When it comes to clerical occupations, it's important to distinguish between jobs that involve more advanced administrative tasks and those that involve less sophisticated procedures. In the first category, "Statistical, finance, and insurance clerks" and "Accounting and bookkeeping clerks" have seen an increase of 3.8 and 3 times respectively.

In the second category, "Clerical support workers not elsewhere classified" have seen an increase of 8.7 times, making this the fastest growing medium-skill occupation. Noticeably, this growth is much more pronounced in Umbria than in Italy as a whole. Additionally, "Secretaries" with an increase of 3.9 and "Receptionists" with an increase of 3.2 are two other clerical roles that perform less sophisticated administrative tasks.¹³ For these two roles the growth is much more comparable to the growth in Italy as a whole. Additionally, one of the emerging occupations is another one of those clerical roles: general office clerks which increased nearly tenfold,.

Finally, another one of the clerical roles, *Stock clerks* which increased 5.3 times, can be seen as one facet of the logistical roles within a firm. Another logistical medium-skill occupation that is in high demand is that of *Heavy truck and lorry drivers*, which increased 2.7 times. The logistics sector is an interesting case, as not only is it a large sector in Umbria, but there are also a few fast-growing occupations, both at the medium-skill and the low-skill level, see Box 1.5.

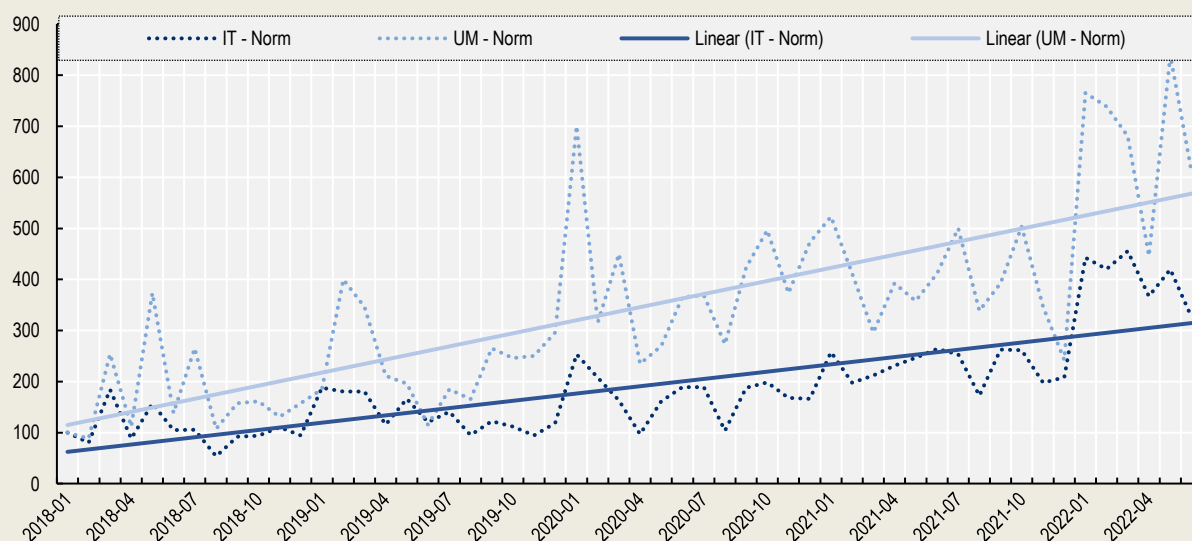
Box 1.5 Fast-growing occupations in the logistics sector

The logistics sector was one of the least negatively impacted by the COVID-19 crisis compared to other economic sectors. Social distancing measures and long queues in brick-and-mortar stores have prompted many retailers to shift their focus to e-commerce digital stores, reducing the role of distributors. According to a recent report by the Observatory on Contract Logistics hosted by the Polytechnic University of Milan, the logistics sector is experiencing a growth rate of 2.8% in 2022, building on an already positive growth rate of 4.7% over 2020 (Frosi, 2021^[16]). At the same time data from the LFS shows that the share of people that work as transport and storage labourers has also increased by 0.35% in between 2018-2021. The share of OJPs looking for these types of workers did increase by 0.7% in the same time period. The positive trend is also reflected at the local level where, anecdotally firms are constantly on the hunt for new, and possibly young personnel (Perugia Today, 2022^[17]).

For these reasons, Figure 1.7 depicts the time-series of three ISCO-08 4-digit occupational codes, related to the logistics sector that provide opportunities for the PES to help unemployed Umbrians find employment: *Stock clerks* (code 4321), *Heavy truck and lorry drivers* (code 8332) and *Freight handlers* (code 9333). *Stock clerks* are endowed with the task of maintaining records of goods produced and production materials received; *Heavy truck and lorry drivers* instead drive and tend heavy motor vehicles to transport goods, liquids and heavy; *Freight handlers* pack, carry, load and unload goods.¹⁴

The relative importance for these occupations in Umbria compared to Italy as a whole is confirmed by the faster growth in Figure 1.7. The series appears to take-off in January 2020 and proceeds by being relatively stable around an index of four times the initial level of January 2018 for the whole 2021. It then spikes again in January 2022. In April 2022 the number of OJPs decreased but remained more than 4 times larger than in 2018, and well above the level in April of 2021. Lightcast data, therefore, confirm the increasing demand of individuals to be recruited in the logistic sector in various roles.

Figure 1.7. Trend of fast-growing logistic-related occupations



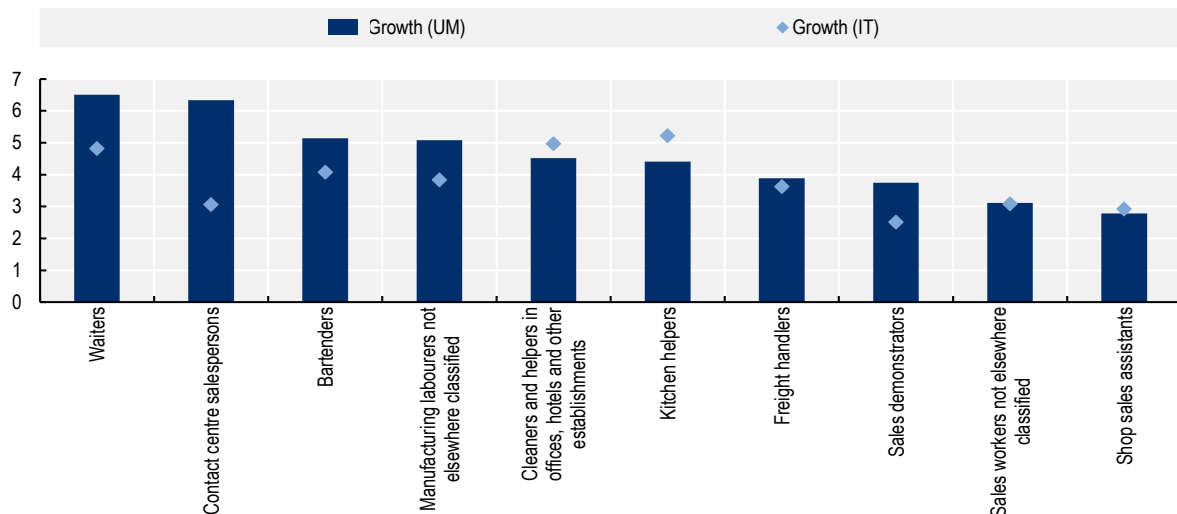
Note: The series combines OJPs related to three ISCO-08 4-digit occupational codes: Stock clerks (code 4321), Heavy truck and lorry drivers (code 8332) and Freight handlers (code 9333). Linear trends are calculated on a standardised index Jan-2018 = 100.

Source: OECD calculations based on Lightcast data; (Frosi, 2021^[16]); (Perugia Today, 2022^[17]); ISCO-08.

Low-skill occupations with increasing demand in online job postings

The fastest growing low-skill occupations increased between 6.5 and 2.8 times (Figure 1.8), which means that the growth rates are less spread out than for the medium- and high-skill occupations. As mentioned previously, low-skill occupations are characterized by a higher volatility in demand, leading to more pressure on the public employment system. At the same time, helping unemployed people transition into low-skilled occupations can be easier for the PES, considering the requirements for these types of jobs. This will be discussed in more detail in the next subsection.

Figure 1.8. Top 10 fast-growing Low-Skill occupations at the ISCO-08 4-digit by growth



Note: Bars represent the growth for each occupation expressed as a simple ratio between the average number of OJPs in the first semester of 2022 over the average number of OJPs posted in the first semester of 2018. Dots overlaying each bar show the equivalent growth of the same occupation for the Italian territory. The occupations displayed have an average number of OJPs above the overall mean of 7.92 OJPs per month. Source: OECD calculations based on Lightcast data.

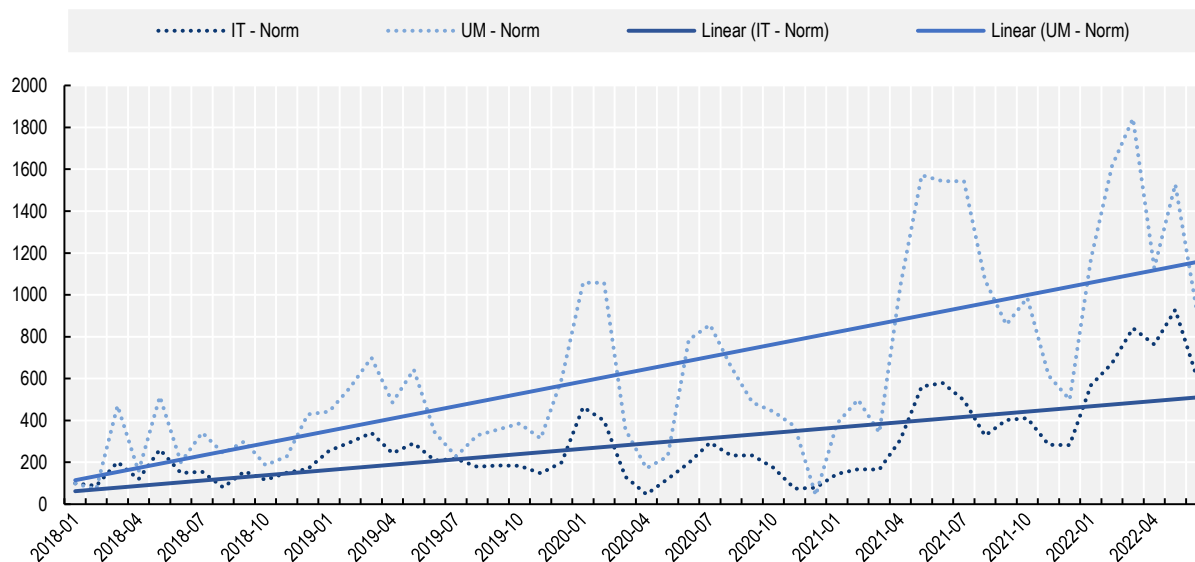
Two occupational areas stand out within Figure 1.8: sales and the food service industry. *Contact centre salespersons*, *Sales demonstrators*, *Shop sales assistants*, and *Sales workers not elsewhere classified* represent three different channels through which employers put forward their sale strategies: by phone, on specific premises like exhibitions or market fairs, and in brick-and-mortar stores. All these roles are tasked to present goods, assist customers in their choices and sell goods on behalf of retailers. These occupations, while closely related, were affected differently by the COVID crisis. On the one hand the risk of infection while carrying out face-to-face interactions increased the need for online sales activities or sales over the phone. This could have a positive impact on the number of OJPs for *Contact centre salespersons*. On the other hand, the ability to curb the rate of infections via the vaccine roll-out allowed live interactions to be restored, which could have had a positive effect on the demand for *Sales demonstrators* and *Shop sales assistants*. Furthermore, domestic demand in Italy, and most likely Umbria as well increased in the first half of 2022, leading to an estimated total increased economic output of 3.9% in 2022 (European Commission, 2023_[18]). This can also be result in increased demand for sales personnel.

Fast-growing Low-skilled occupations within the food service industry are *waiters*, *kitchen helpers* and *bartenders*. *Waiters* are the top fast-growing occupation in this category moving from an average number of 7 posts a month in the first semester of 2018 to an average of about 47 posts per month in the first semester of 2022, representing a six-fold increase. In a related fashion the demand for *Bartenders* has moved from an average of 3.5 OJPs per month to an average of 18 OJPs per month for the same period, revealing a volume of demand five times higher in 2022. *Kitchen helpers* follow, with a similar increase of 4.4 times during the period, made by an average volume of OJP of about 30 in the first semester of 2022 with respecting to the starting point of about 7 in the same semester of 2018.

The high demand for food industry workers after 2021 reflects the success story of post-COVID tourism in the Umbria region that, according to the observatory on tourism of the Umbria region, has welcomed a record number of tourists in 2021 and 2022 (Regione Umbria, 2022_[19]). In general, food industry jobs are characterised by a high level of volatility, and a demand which is quite seasonal in nature (Figure 1.9). The right end of the Umbrian graph shows a great spike in OJPs for waiters, kitchen helpers and bartenders

between March 2021 and September 2021 and a second spike in March 2022 evolving over Q2 2022 summer in a similar fashion. The growth is much more pronounced for Umbria than for Italy as a whole.

Figure 1.9. Trend of fast-growing food-industry occupations



Note: The series combines OJPs related to three ISCO-08 4-digit occupational codes: Waiters (code 5131), Kitchen helpers (code 9412) and Bartenders (code 5132). Linear trends are calculated on a standardised index Jan-2018 = 100. The Lightcast dataset ends in June of 2022. The data collection is usually followed by a process of data-refinement that can last months; for this reason the last few points of the series should not be interpreted as a decline in this occupational category.

Source: OECD calculations based on Lightcast data.

What are the job characteristics of fast-growing and emerging occupations?

Public employment systems heavily invest resources in training courses for people with low employment prospects, in order to help them exit the unemployment pool. In order to show the average profile that employers are looking to hire, this section looks at *required educational background* and *required experience* for different types of jobs. Additionally, this section offers a descriptive view of *the contractual stability*¹⁵ of the offered contract and of the *working hours*, to assist the PES with fine-tuning jobseekers' expectations on what types of contracts they can expect to receive. Consistently with the previous analysis, a distinction is made between profiles and contracts for occupations at different skill levels.

Comparison of High, Medium and Low-skilled occupations

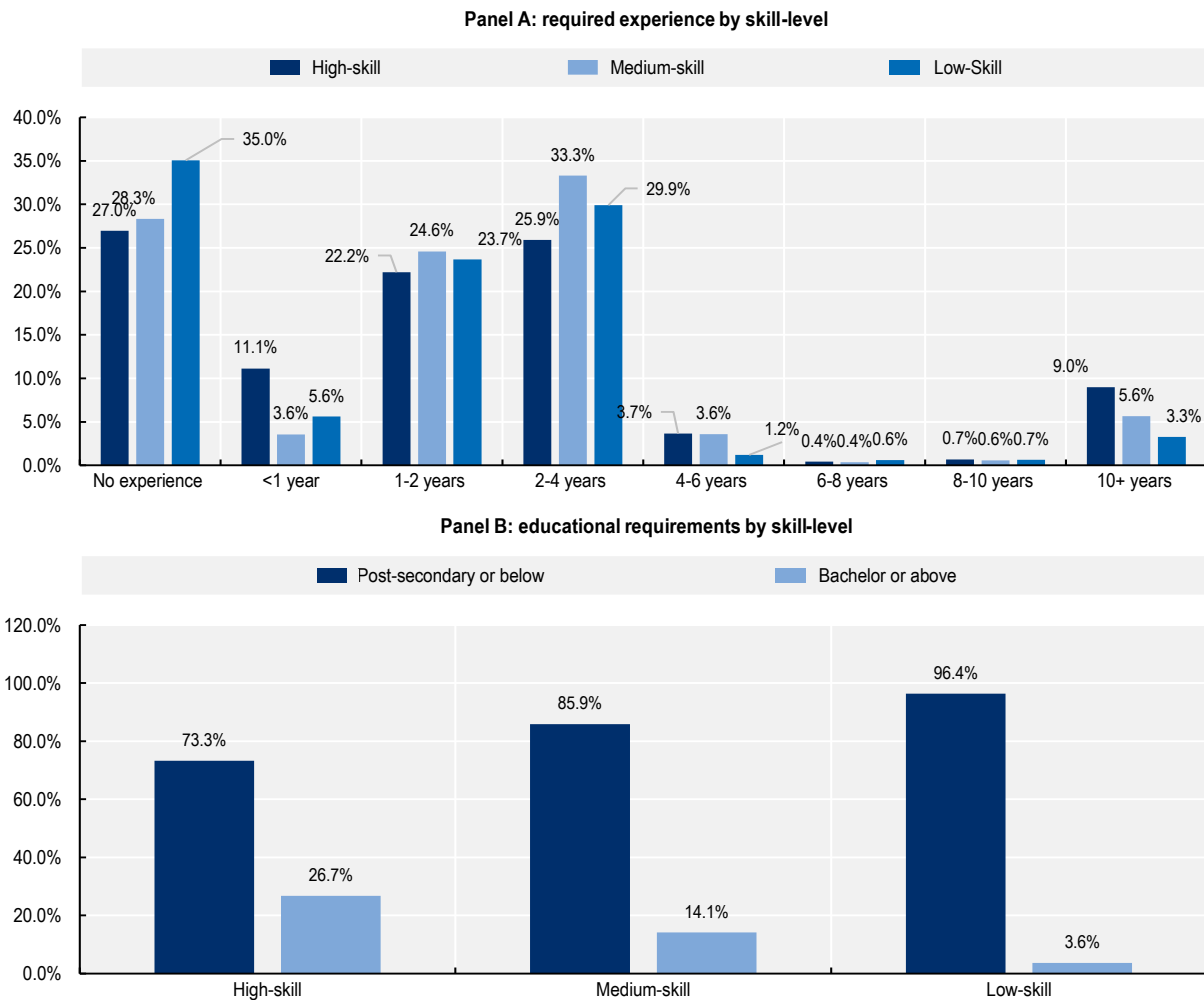
In general, the OJPs for low-skilled occupations in Umbria require fewer years of experience than OJPs for either medium- or high-skilled occupations, as can be seen in Figure 1.10, Panel A. The majority of OJPs for low-skilled occupations specify that candidates should have zero to four years of experience. 35% of the online vacancies for low-skilled positions even require *No Experience* dedicated to them.

Yet, an important share for high-skilled occupations also consists of entry-level positions, as 10% of the vacancies are open to workers with a *1-year experience*, and 27% to workers with *No experience*, suggesting an important role for internships or traineeships in this type of vacancies, which is further explored below.

The right side of Panel A shows that the vacancies for high-skilled occupations often require more experience. OJPs dedicated to candidates with ten or more years of experience are about 9% in high-skilled occupations, followed by 6% for medium- and 3% for low-skilled occupations.

In terms of *educational level*, which can be seen in Panel B of Figure 1.10, the results are as expected: high-skilled occupations require a higher education. Roughly one third of their vacancies are specifically looking for candidates with a bachelor's degree or higher qualification. The same requirements are instead rarely asked for low-skilled occupations (3.6%), and medium-skilled occupations (14.1%).

Figure 1.10. Expected candidate profile – comparison of high-, medium- and low-skilled occupations



Note: NAs constitute 59% of the sample for the required experience, and 0.1% for the education requirements.

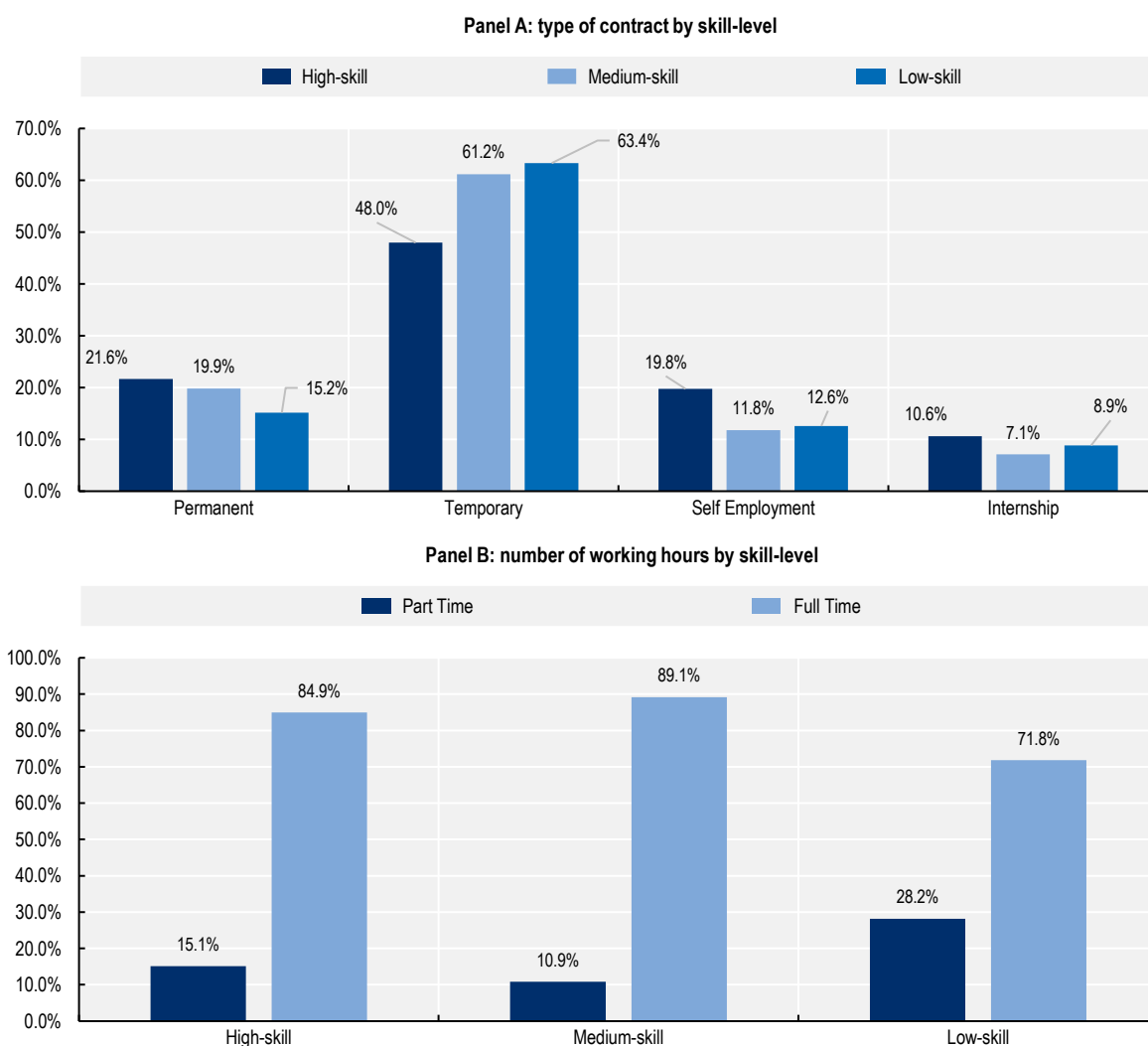
Source: OECD calculations based on Lightcast data.

Based on the analysis of online job postings, it appears that the number of permanent contracts offered by employers is relatively similar across all skill levels, although low-skilled workers are less likely to be offered a permanent contract (Figure 1.11 Panel A). In terms of contractual stability, the largest difference is seen for self-employed contracts, with OJPs for high-skilled occupations more likely to look for workers in this category. Temporary contracts are offered in just above 60% of vacancies for both medium- and low-skilled occupations, compared to 49% for high-skilled occupations. However, the difference in temporary contracts is not compensated by permanent contracts but by self-employment, indicating that a significant

portion of fast-growing high-skilled occupations can be considered as consultancy roles rather than actual employment.

Regarding the working hours, the largest imbalance between part-time and full-time contracts is in the low-skill category, where the former covers a share of 28% and the latter of 72% (panel B of Figure 1.11). In contrast high-skilled and medium-skilled occupations offer *part-time* contracts 14% and 11% of the time. Contributing to the lower prevalence of full-time contracts for low-skill occupations, could be the high-degree of substitutability in skill and the seasonal nature of these jobs. Employers benefit from offering employees flexible contracts, allowing them to access workers almost on demand, whenever the workload exceeds expectations.

Figure 1.11. Offered contract characteristics – comparison of high-,medium-. and low-skilled occupations



Note: NAs constitute 14% of the sample for the contract types, and 25% for the number of working hours.

Source: OECD calculations based on Lightcast data.

Comparing requirements and contractual characteristics of occupations *between* skill levels allows to understand similarities and differences that can be crucial in the design of training offers that serve to align expectations between supply and demand. Yet, *within* skill-level, there is still quite a lot of heterogeneity between occupations, details on job characteristics per skill-level can be found in Annex 1.A.

Demand and supply on the labour market: OJPS versus employment data

The analysis of OJPs offers a unique opportunity to investigate labour market demands. The previous sections are an example of the types of insights that can be generated by using data that is detailed for many different occupations and is updated frequently. OJPs data can show occupation-specific trends and heterogeneity between different occupations, and easily track this on a month-to-month basis.

Yet, online job postings cannot inform on the supply side of the labour market and on actual employment. Additional information can be gathered from employment data. In this subsection the analysis of Umbria's OJPs is complemented by data specific for this region from the EU – Labour Force Survey (LFS) in the period 2018-2021. This is to say that, while OJPs provide information on the strength of the demand (as new vacancies can be interpreted as the desire of employers to hire), the LFS offers insights on the volume of individuals that are actually employed in a certain occupation (that is when employers have found the right candidates and their desire to hire have been fulfilled).

In terms of statistical granularity, it's important to note that the LFS data is less detailed compared to the Lightcast data. The LFS provides a representative snapshot of employment over the course of a year, whereas the Lightcast dataset tracks labour demand in near real-time through online job postings. Additionally, the LFS only offers data at the ISCO-08 three-digit level due to sample size limitations, which is less specific than the four-digit level that the OJPs provide.

The comparison between data from OJPs and the LFS can provide valuable insights. However, there may be a mismatch between the two datasets. Lightcast data relies on online job postings, which may not represent all types of roles and occupations in the labour market. The LFS data, instead, can be used to check the representativeness of the online landscape for the entire labour market.

Additionally, the comparison between the two datasets can provide signals on the emergence of potential shortages in the labour market. If there are more OJPs for a certain position than the number of people currently performing that role, it could suggest difficulties for the supply side to adjust to the needs of the demand side, resulting in unfilled vacancies. Alternatively, it could suggest high labour turnover in that role, where many employees leave their positions and are replaced by new employees, which does not necessarily indicate labour shortages.

The first part of this subsection addresses the representativeness of the Lightcast data comparing the share of OJPs by occupation with the share of people employed. The LFS data here can be seen as showing relevancy of different occupations in the labour market as a whole. The second part focuses more on the dynamics on the labour market. It expands on why certain differences are detected, assessing the possibility that the gaps found can be attributed to a tightness on the labour market, that is whether employers will have a harder time when trying to find employees.

A discussion of the representativeness of OJPs against LFS data

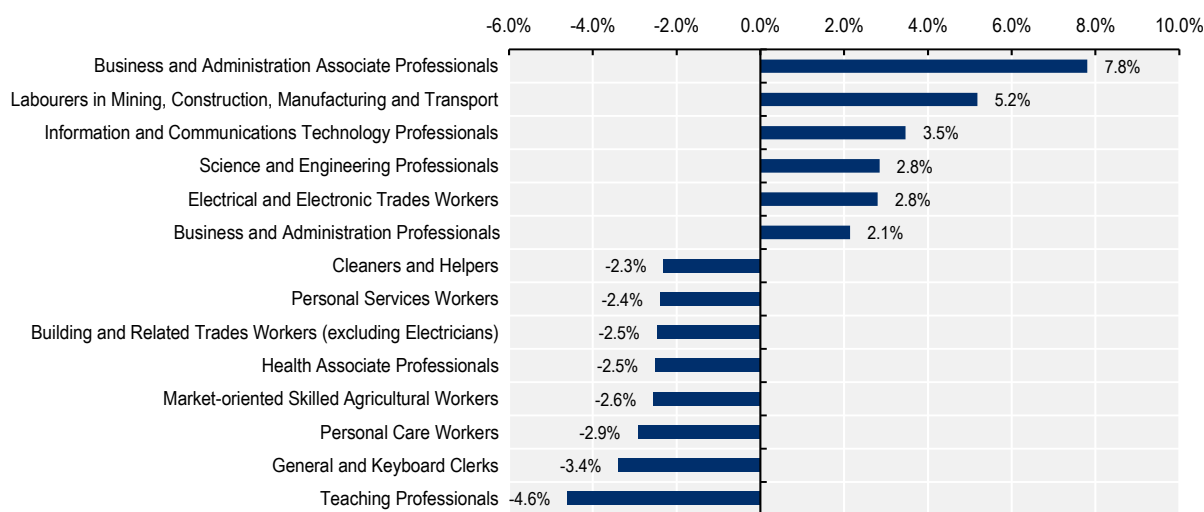
To assess representativeness, the benchmark measure used is a comparison between the percentage share of individuals employed in a certain occupation in the LFS data with the percentage share of OJP in the Lightcast data, for the same occupation, during the entire period of analysis (Cammeraat and Squicciarini, 2021^[20]). Comparing the stock of employed with the stock of vacancies gives, to a first approximation, a sense of the occupational codes for which the OJP data are unbalanced.

One important caveat to this analysis is that for the Umbria region specifically, it cannot be guaranteed that the benchmark of the LFS data is fully representative of the real employment situation in the region. While the LFS is representative on a country level, it could be the case that within the specific region of Umbria, certain occupations are under- or overrepresented, when compared to the actual working population. This analysis should therefore be interpreted as indicative of how representative the OJPs are for the total labour market landscape rather than conclusive.

The comparison unveils three imbalances worth discussing. Firstly, occupations that require public selection are less represented in the Lightcast data than in employment data. For example, Teaching Professionals cover a share 4.4% higher in the LFS data than in the Lightcast dataset, followed by Health Associate Professionals with an imbalance of 2.6% (Figure 1.12). The public selection process is in place to assure the required level of professionalism from the future government employee and is required by law for every publicly financed institution in Italy (Ministro per la Pubblica Amministrazione, 2015^[21]). This means that teaching positions in public schools and roles in the public health system both are recruited via public selection.

Secondly, occupations which require a direct human contact between the employer and the employee, such as Personal Care Workers, and Cleaners and Helpers, seem to be less in terms of OJPs, with an imbalance of 3% and 2.2% respectively. Vacancies for these occupations might be better advertised through word of mouth given the level of trust required, on the part of the employer, to allow the worker to operate in her own personal space.

Figure 1.12. Difference in volume between LFS and OJP at the ISCO-08 2-digit for the years 2018-2021



Note: The bar-chart shows the difference between the percentage share that each occupation covers in the Lightcast data and the percentage share that the same occupation covers in the LFS data, at the ISCO-08 2-digit level for the years 2018, 2019, 2020 and 2021 pooled together. A positive number indicates a higher percentage share, for each occupation, in the Lightcast dataset; a negative number instead represents a higher share in the LFS data than in the Lightcast data. Only occupations with an absolute difference above 2% are shown.

Source: OECD calculations based on Lightcast data and EU-LFS data aggregating the period 2018-2021.

Thirdly, certain occupations seem to be overrepresented in the Lightcast data. Jobs as Business and Administration (Associate) Professionals are more present in OJPs than in employment data. Focusing on jobs that seem to be overrepresented, Table 1.2 reports the top 10 list of occupations, this time at the 3rd digit of the ISCO-08 classification, ranked by the highest difference in share between the LFS and the Lightcast data. Seven out of ten positions are filled by various types of high-skill occupations, mostly business professionals, such as Sales and purchasing agents and brokers, Administrative and specialised secretaries and Business services agents, along with technical occupations, such as Software and applications developers, Engineering professionals, and Physical and engineering science technicians. Cammeraat and Squicciarini (2021^[20]) previously showed similar overrepresentation of professionals and technicians in OJPs data for the US, UK, Canada, Australia, Singapore and New Zealand. This is possibly due to higher propensity of employers to post these types of vacancies online. This behaviour results in a higher probability to encounter these occupations in the Lightcast data. As was mentioned in section 1, Carnevale, Jayasundera and Repnikov (2014) estimate that around 80-90% of postings requiring at least a bachelor's degree can be found online, whereas 40-60% of job postings requiring a high school degree are advertised on the internet.

Table 1.2. Top 10 Occupations at the ISCO 3-digit with highest difference in share between LFS and Lightcast, for the period 2018-2021

| ISCO-08 3-d | ISCO-08 3-d Name | Share (LFS) | Share (Lc) | Difference |
|-------------|---|-------------|------------|------------|
| 933 | Transport and storage labourers | 0.83% | 4.39% | 3.56% |
| 251 | Software and applications developers and analysts | 0.42% | 3.90% | 3.48% |
| 214 | Engineering professionals (excluding electrotechnology) | 1.02% | 4.16% | 3.14% |
| 332 | Sales and purchasing agents and brokers | 2.22% | 5.10% | 2.88% |
| 334 | Administrative and specialised secretaries | 0.48% | 2.93% | 2.46% |
| 311 | Physical and engineering science technicians | 2.05% | 4.44% | 2.40% |
| 243 | Sales, marketing and public relations professionals | 0.69% | 2.91% | 2.22% |
| 741 | Electrical equipment installers and repairers | 1.30% | 3.41% | 2.10% |
| 333 | Business services agents | 1.03% | 3.00% | 1.97% |
| 932 | Manufacturing labourers | 0.47% | 2.15% | 1.68% |

Source: OECD calculations based on Lightcast and EU – Labour Force Survey data.

Another discrepancy that stands out is the overrepresentation of transport and storage labourers (difference of 3.6 percentage points). In this situation it is more likely that dynamics on the labour market are at play. For instance, when employment (in the LFS data) does not track demand (in the Lightcast data) this could be due to the existence of a supply-shortage. This suggests that not enough workers are available to fulfil the demand, creating an imbalance of OJPs that does not translate to actual jobs.

The likelihood of a vacancy being posted online and the dynamics on the labour market contribute jointly to overrepresentation, and disentangling the precise reasons is not always possible.

Combining OJPs and LFS data to get insights about labour shortages

The labour market is not static, supply and demand change from month to month and year to year. To capture these fluctuations on a yearly basis, this section discusses the construction of a preliminary

tightness indicator that tries to combine information on the volume of OJPs with that of employed individuals by occupation and over time.

In a nutshell, the objective of the proposed tightness indicator is to build a measure of general tightness of the labour market in a certain year. To do so, it first calculates the relative ease or difficulty with which employers can hire employees for a specific occupational group, by comparing its tightness to the general tightness on the entire labour market in each year. Lastly, for ease of interpretation, the relative tightness per occupation in 2018 is used as a benchmark to follow the developments per occupation in each year. Caution needs to be exercised in interpreting the results from the tightness indicator, as of course both the LFS and the Lightcast data have limitations. Technical details of the calculation can be found in Box 1.6.

Box 1.6. A tentative indicator of labour market tightness combining OJPs and LFS data

The goal of the tightness indicator is to calculate the relative ease with which employers can hire employees for certain occupational groups, relative to the general labour market, and relative to the situation for that occupational group in 2018. To observe the tightness for a certain occupation in a specific year t , it is first necessary to know how tight the labour market in general is.

For this purpose, the general tightness, GT_t , is calculated as follows: $GT_t = \frac{\sum_i LC_{it}}{\sum_i LFS_{it}}$. In this equation, LC_{it} measures the number of OJPs for occupational group i in year t , likewise LFS_{it} measures the number of people in the LFS data that indicated working in occupational group i in year t .

Next, the tightness per occupational group i relative to the entire labour market is measured by: $RT_{it} = \frac{LC_{it}/LFS_{it}}{GT_t}$. A relative tightness larger than 1 indicates that the situation for that occupation is tighter than the situation in the general labour market, while a value below 1 indicates that it is relatively easier to find employees for that occupation than it is to find employees on the labour market in general.

Lastly, the tightness indicator TI_{it} is calculated by indexing the relative tightness in 2019, 2020 and 2021 to the relative tightness in 2018. A value above 1 means that the number of OJPs compared to the number of people employed in a certain occupational group, relative to the general tightness, grew compared to that same number in 2018. A value below 1 indicates that the labour market for those positions got slacker compared to the situation in 2018.

The analysis focuses on the ten occupational groups that had the largest shares of OJPs in 2021, which jointly represent 32.5% of all OJPs in 2021. These groups are considered a substantial part of the total number of vacancies posted online. The dynamics of these specific groups are analysed in Table 1.3.

The results show that all the occupations in Table 1.3, with the exception of shop salespersons and domestic, hotel and office cleaners and helpers, had tighter than average labour markets in both 2018 and 2021.¹⁶ This is a preliminary indication that the volume of OJPs for these positions relative to employment is higher than in other positions, signalling that it is relatively hard to find workers to fill vacancies for those jobs.

Only three out of the ten largest occupations in terms of OJPs record tighter labour markets in 2021 relative to 2018, as can be seen from the column labelled “2021”. Results suggest a tighter labour market for Physical and engineering science technicians, Software and applications developers and analysts, and the previously mentioned domestic, hotel and office cleaners and helpers. Results for some of these occupations, however, need to be interpreted with caution as Physical and engineering science technicians, Software and applications developers and analysts technical occupational groups are likely overrepresented in OJPs, potentially biasing upward the values of the tightness indicator.

The indicator on the other hand seems to suggest that labour market for the other technical professional occupational group in the top 10, that of engineering professionals (excluding electrotechnology), has by contrast become less tight in 2019, 2020 and 2021 compared to 2018.

The other seven out of ten largest occupations in terms of shares of OJPs did see fluctuations over time, but the indicator built on the combination of OJPs and LFS data does not seem to suggest a tighter labour market demand for them in 2021 compared to 2018 (although these are still tighter than the general labour market on average in both years). For example, the tightness indicator for transport and storage labourers peaked in 2020, and it is still larger than average in 2021, but tightness has decreased in intensity relative to 2018. This could mean that in between the LFS in 2020 and 2021 more people have been employed as transport and storage labourers, or that the demand for them has decreased. Even a position such as Electrical equipment installers and repairers, which was around 60% less tight in 2019, 2020 and 2021 compared to 2018, still has relatively more demand compared to employees than what is observed in the average labour market.

Table 1.3. Tightness indicator for the largest occupations in terms of share of OJPs in 2021

| ISCO08_3D | Label | 2019 | 2020 | 2021 |
|-----------|---|------|------|------|
| 933 | Transport and storage labourers | 1.10 | 1.31 | 0.81 |
| 214 | Engineering professionals (excluding electrotechnology) | 0.77 | 0.71 | 0.84 |
| 311 | Physical and engineering science technicians | 0.92 | 1.09 | 1.22 |
| 332 | Sales and purchasing agents and brokers | 0.87 | 0.90 | 0.70 |
| 251 | Software and applications developers and analysts | 0.92 | 0.94 | 1.52 |
| 741 | Electrical equipment installers and repairers | 0.58 | 0.60 | 0.57 |
| 522 | Shop salespersons | 0.81 | 0.69 | 0.57 |
| 911 | Domestic, hotel and office cleaners and helpers | 1.03 | 1.55 | 1.42 |
| 243 | Sales, marketing and public relations professionals | 1.20 | 0.71 | 0.99 |
| 431 | Numerical clerks | 1.37 | 0.80 | 0.76 |

Note: the ratios have been calculated using the method described in Box 1.6. A. Values above 1 indicate that the number of OJPs compared to the number of people employed in a certain occupational group, relative to the general tightness, grew compared to that same number in 2018. Source: OECD calculations based on Lightcast and EU – Labour Force Survey data.

References

- Cammeraat, E. and M. Squicciarini (2021), “Burning Glass Technologies’ data use in policy-relevant analysis: An occupation-level assessment”, *OECD Science, Technology and Industry Working Papers*, No. 2021/05, OECD Publishing, Paris, <https://doi.org/10.1787/cd75c3e7-en>. [20]
- Carnevale, A., T. Jayasundera and D. Repnikov (2014), *Understanding Online Job Ads Data*, Center on Education and the Workforce, <https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech.Web.pdf>. [5]
- European Commission (2023), *Economic forecast for Italy*, https://economy-finance.ec.europa.eu/economic-surveillance-eu-economies/italy/economic-forecast-italy_en (accessed on February 2023). [18]
- European Commission (2022), *Organisation of post-secondary non-tertiary education*, <https://eurydice.eacea.ec.europa.eu/national-education-systems/italy/organisation-post-secondary-non-tertiary-education> (accessed on February 2023). [22]
- European Commission (2020), *European Network of Public Employment Services - Upskilling, reskilling and prevention in times of crisis*, <https://ec.europa.eu/social/BlobServlet?docId=23325&langId=en>. [4]
- Frosi, D. (2021), *La Logistica in Italia: mercato, numeri e trend evolutivi*, https://blog.osservatori.net/it_it/mercato-logistica-italia (accessed on January 2023). [16]
- Gostoli, Y. (2020), *Short on doctors, Italy looks to migrants*, <https://www.dw.com/en/coronavirus-short-on-doctors-italy-looks-to-migrants/a-55789791> (accessed on February 2023). [13]
- Hershbein, B. and L. Kahn (2016), *Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings*, National Bureau of Economic Research, Cambridge, MA, <https://doi.org/10.3386/w22762>. [6]
- INSOL Europe (2022), *Osservatorio Fallimenti, Procedure e Chiusura d’Impresa [Observatory Bankruptcies, Procedures and Business Closures] Q1 2022*, <https://www.insol-europe.org/download/documents/2416>. [11]
- INSOL Europe (2021), *Osservatorio Fallimenti, rocedure e Chiusura d’Impresa [Observatory Bankruptcies, Procedures] Q3 2021*, <https://www.insol-europe.org/download/documents/2186>. [10]
- Istat (2022), *Conti Economici Territoriali, Anni 2019-2021 [Territorial Economic Accounts, 2019-2021]*, https://www.istat.it/it/files/2022/12/REPORT-CONTI-TERRITORIALI_2021.pdf (accessed on January 2023). [2]
- Istat (2020), *Estimated resident population - Years 2001-2019 : Umbria 3*, <http://dati.istat.it/Index.aspx?QueryId=12400&lang=en> (accessed on February 2023). [3]
- ITA (2022), *Italy - eCommerce*, <https://www.trade.gov/country-commercial-guides/italy-ecommerce> (accessed on December 2022). [26]
- Manica, M. et al. (2021), “Impact of tiered restrictions on human activities and the epidemiology of the second wave of COVID-19 in Italy”, *Nature Communications*, Vol. 12/1, <https://doi.org/10.1038/s41467-021-24832-z>. [25]

- Ministro per la Pubblica Amministrazione (2015), *Concorsi ed assunzioni*, [21]
<https://www.funzionepubblica.gov.it/lavoro-pubblico-e-organizzazione-pa/concorsi-ed-assunzioni> (accessed on February 2023).
- OECD (2021), *OECD Skills Outlook 2021: Learning for Life*, OECD Publishing, Paris, [7]
<https://doi.org/10.1787/0ae365b4-en>.
- OECD (2019), *OECD Employment Outlook 2019: The Future of Work*, OECD Publishing, Paris, [24]
<https://doi.org/10.1787/9ee00155-en>.
- OECD (2019), *Strengthening Active Labour Market Policies in Italy*, Connecting People with Jobs, OECD Publishing, Paris, [1]
<https://doi.org/10.1787/160a3c28-en>.
- Paolucci, G. et al. (2021), "Impact of the COVID-19 pandemic and work-related stress in Umbrian healthcare workers during Phase 1 in Italy", *Medicina del Lavoro*, [12]
<https://doi.org/10.23749/mdl.v112i6.12285>.
- Perugia Today (2022), *Informatica e mondo digitale, un protocollo d'intesa tra l'Itet Capitini di Perugia e Confcommercio per orientare i giovani alle professioni digitali*, [15]
<https://www.perugiatoday.it/formazione/scuola/informatica-protocollo-intesa-itet-capitini-perugia-confcommercio-orientare-giovani-professioni-digitali.html> (accessed on January 2023).
- Perugia Today (2022), *L'azienda umbra che batte la crisi: Servizi Associati. Più 500 assunzioni, nuove commesse e fatturato in crescita. "Cerchiamo altro personale"*, [17]
<https://www.perugiatoday.it/economia/umbria-servizi-associati-boom-assunzioni-2022-battuta-la-crisi-fatturato-in-crescita.html> (accessed on January 2023).
- Pippi, R. and C. Fanelli (2021), "Is physical activity a necessary element during Italian coronavirus disease emergency? Yes or no debate", *Journal of Human Sport and Exercise*, [9]
 Vol. 17/4, <https://doi.org/10.14198/jhse.2022.174.09>.
- Polizia Di Stato (2020), *La carta di qualificazione del conducente professionale*, [23]
https://www.poliziadistato.it/articolo/10543-La_carta_di_qualificazione_del_conducente_professionale (accessed on February 2023).
- Ravalli, S. and G. Musumeci (2020), "Coronavirus Outbreak in Italy: Physiological Benefits of Home-Based Exercise During Pandemic", *Journal of Functional Morphology and Kinesiology*, [8]
 Vol. 5/2, p. 31, <https://doi.org/10.3390/jfmk5020031>.
- Regione Umbria (2022), *Flussi turistici nel mese di Ottobre, 10 mesi e semestre maggio-ottobre 2022-21-20*, <https://www.regione.umbria.it/turismo-attivita-sportive/statistiche-turismo-2022> [19]
 (accessed on January 2023).
- Umbria Domani (2022), *In Umbria cresce la domanda di professionisti ict e digitali, ma mancano le figure adatte*, <http://www.umbriadomani.it/economia/in-umbria-cresce-la-domanda-di-professionisti-ict-e-digitali-ma-mancano-le-figure-adatte-283885/> [14]
 (accessed on January 2023).

Annex 1.A. Job characteristics per skill-level

High-skill occupations

In general, high-skilled occupations show high barriers to entry in terms of years of experience and high diploma requirements. The scope for retraining existing human capital to meet employers' expectation appears to be limited. However, these generalisations hide a level of heterogeneity as for young talents and, in turn, for the public employment system, the opportunity lies in entry level programs that could facilitate the transition from school to work.

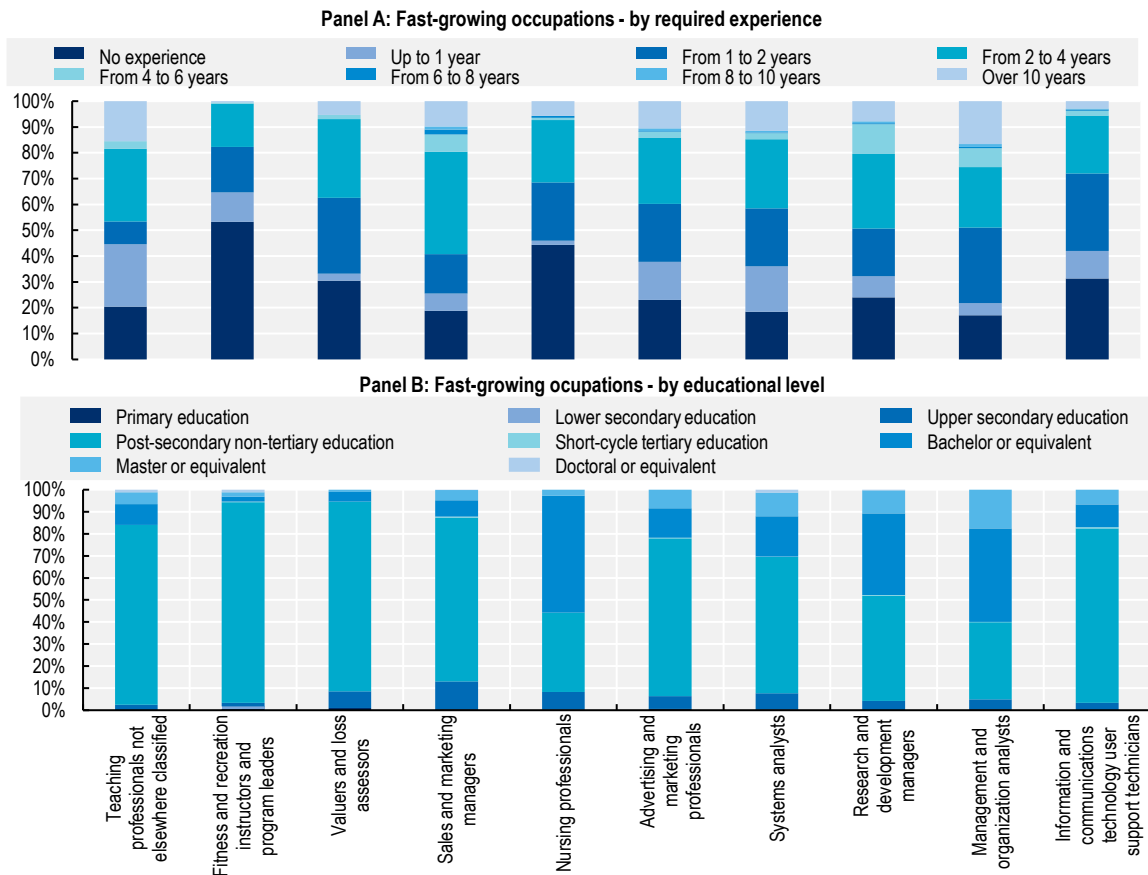
Most of the OJPs for high-skilled occupations that search for candidates with multiple years of experience, consist of vacancies dedicated to for example managerial positions (Annex Figure 1.A.1.). Among the ten fast-rising and emerging occupations, *Sales and marketing managers*, *Research and development managers* and *Management and organization analysts* open in between 20 to 30% of their vacancies to candidates with more than 4 years of experience.

On the other hand, a significant share of fast-growing IT and health-related vacancies are open to candidates with very little experience. This result is potentially driven by the COVID-19 crisis, to the extent that, for IT professionals, it has spurred firms to accelerate the digital conversion of many production tasks. For health-professionals, it has required a vaccination rollout of massive scale. In fact, Panel A of Annex Figure 1.A.1 shows how employer in the hunt for *Nursing professionals* and *Information and communications technology user support technicians* dedicate up to 40% to entry-level candidates in the form of *No-experience*.

The educational level required for high-skill jobs is the second barrier to entry, and only partially mirrors the experience requirements. Panel B of Annex Figure 1.A.1 suggests how some professions more than other consider a higher education as a crucial requirement. In fact, *Nursing professionals*, *Management and organization analysts* and *Research and development managers* feature a share ranging from 50 to 60% of vacancies dedicated to candidates with a bachelor or more.

The vast majority of the rest of the high-skilled jobs is open to candidates with post-secondary non-tertiary education. In the context of Italy and Umbria, this means that people have followed either courses in the higher technical education and training system (IFTTS) or in the vocational education and training system in the Regions (European Commission, 2022^[22]).

Annex Figure 1.A.1. Top 10 fast-growing High-Skill occupations – Expected Candidate Profile



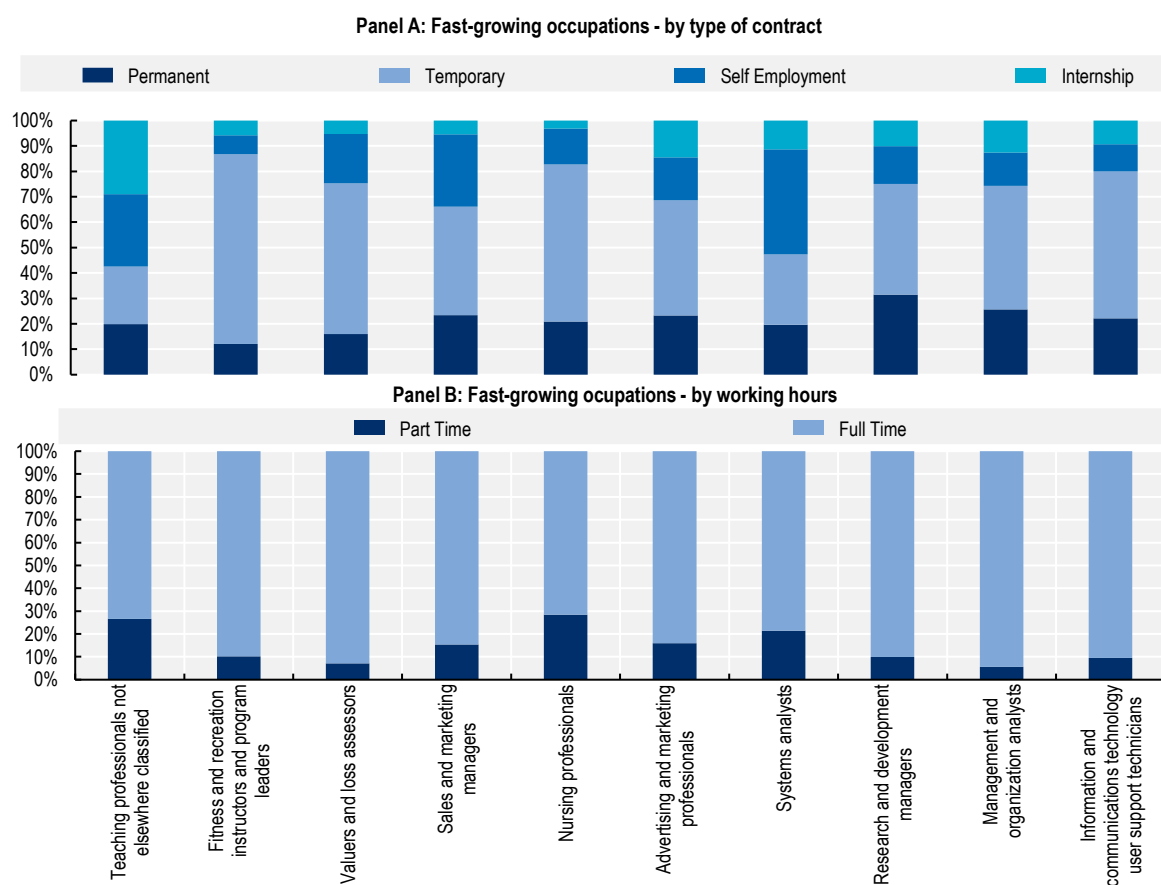
Note: NAs constitute 52% of the sample for experience and 0.1% for education.
Source: OECD calculations based on Lightcast data.

As around 10% of the vacancies for high-skilled jobs in Umbria are open to candidates with up to 1 year of experience, it is good to look at the types of contract high-skilled occupations are offered. Low experience for high skilled occupations hints to an important role for internship and traineeship programs especially for young individuals in a delicate school to work transition. Indeed, especially for occupations in the right end of Annex Figure 1.A.2 panel A, that is, a mixture of IT-based and analyst professions, up to 10% of vacancies are dedicated to internship programs.

Furthermore, in accordance with the previous subsection, for high-skill occupations there are high shares of self-employment contracts. Panel A in Annex Figure 1.A.2 shows how self-employment plays an important role for *System analysts* and *Teaching professionals not elsewhere classified*. These results should not come as a surprise. The formers, *system analysts* are endowed with the task of managing the IT infrastructure, a role often externalized by firms; the latter instead, include teachers who provide privately held lectures and hence are not formally part of a school.

The standard number of working hours for high-skill occupations appears to be a full-time contract (Panel B of Annex Figure 1.A.2). Although there are three notable exceptions: *Nursing professionals*, *Teaching professionals not elsewhere classified* and *System analysts* have around 30% of vacancies dedicated to part-time work. Two of these positions also had a high prevalence of self-employment, which often goes hand-in-hand with a non-traditional workload that is not exactly between 38-40 hours each week.

Annex Figure 1.A.2. Top 10 fast-growing High-Skill occupations – Offered Contract Characteristics



Note: NAs constitute 20% of the sample for type of contract and 31% for working hours.

Source: OECD calculations based on Lightcast data.

Medium-skill occupations

As seen previously, some of the *medium-skilled* occupations showed lower barriers to entry and encompass tasks that appear easier to prepare for in a more limited time span. This opens the door for the public employment system to experiment with training programs that could help certain unemployed individuals to be hired in medium-skill jobs.

According to the ISCO-08 classification, seven out of the ten fast-growing and emerging medium-skill occupations require workers to perform clerical tasks. These clerical jobs can be further divided into two categories. The first category consists of clerical occupations that require a higher level of expertise and a higher level of education. General office clerks, Clerical support workers not elsewhere classified, Stock clerks, Statistical, finance and insurance clerks and Accounting and bookkeeping clerks all belong to this category. As evidenced in Annex Figure 1.A.3, Panel A and B these occupations require both the highest levels of experience and the highest education among the fast-growing medium-skilled occupations. Accounting and bookkeeping clerks are even comparable to high-skill occupations in required experience and education.

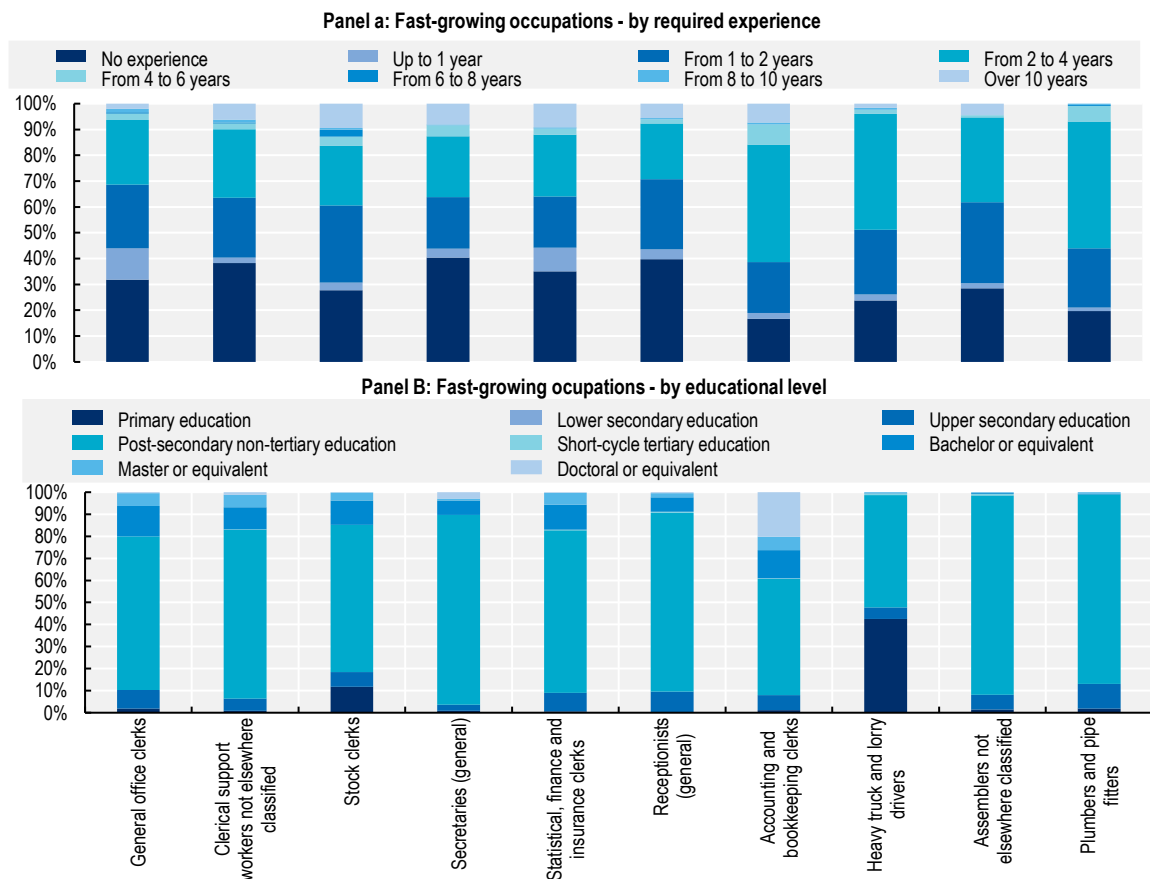
The second category of clerical occupations present an opportunity for the public employment system in terms barriers to entry and of skill conversion. It includes Secretaries (general) and Receptionists (general), which in general have low experience requirements and often do not require tertiary education. This is evidenced by the 40% of vacancies accepting candidates with *No experience* and up to 90% of the vacancies requiring only *post-secondary non-tertiary education*. According to the ISCO-08 classification

Receptionists are endowed with tasks such as receiving and welcoming clients, making appointments, dealing with telephone requests for information or appointments while Secretaries are required to handle correspondence, produce written drafts conformed to office standards, helping to organize meetings etc. The level of tasks required coupled with the low barrier to entry might justify dedicated training programs to endow a specific target of jobseekers with the necessary knowledge of basic typewriting and spreadsheet software helping them to jumpstart their pathways in similar occupations.

For the non-clerical occupations, it stands out that plumbers and pipe fitters are more often required to have from 2 to 4 years of experience, while the majority of positions for assemblers not elsewhere classified are open to people with less than 2 years of experience (Annex Figure 1.A.3, Panel A). Education requirements for these positions are very similar however, with around 90% of OJPs requiring post-secondary non-tertiary education. Plumbers can for example obtain a diploma from a technical institution, or professional qualification.

Heavy truck and lorry drivers are the only job in the top 10 medium-skill occupations that require only primary education in 40% of OJPs. However, this does not mean that there are no requirements in terms of diplomas or qualifications. More important than traditional formal education, in this role it is necessary to have a C driving license, which allows someone to drive motor vehicles for the transport of goods with a total mass exceeding 3.5 tons, or a CE license which allows loads exceeding 3.5 tons up to 7.5 tons. Additionally, heavy truck and lorry drivers need to have a CQC (Carta di Qualificazione del Conducente), which is a driving licence specifically for drivers who professionally carry out the road haulage of goods (Polizia Di Stato, 2020^[23]).

Annex Figure 1.A.3. Top 10 fast-growing Medium-Skill occupations – Expected Candidate Profile



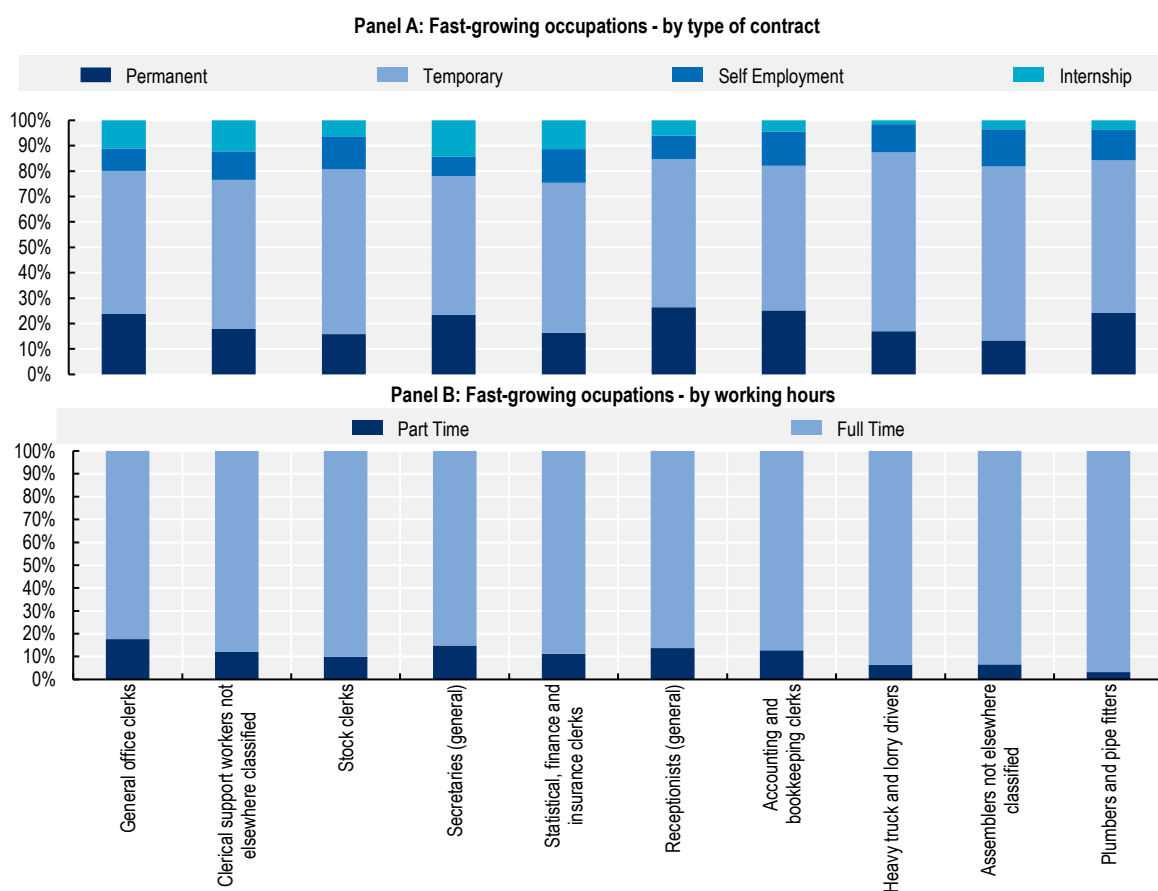
Note: NAs constitute 63% of the sample for experience and 0.1% for education.

Source: OECD calculations based on Lightcast data.

In terms of the types of contracts that are offered, Panel A in Annex Figure 1.A.4 shows that the top ten fastest growing and emerging occupations are very similar to all medium skill occupations. Most contracts are temporary, with around 20% of offered contracts being permanent contracts. Internship positions are most common for secretaries, clerical support workers not elsewhere classified and general office clerks.

Similarly, the share of vacancies offering a full-time contract is just below 90%, which is again perfectly in line with all the other medium-skill occupations (Panel B of Annex Figure 1.A.4). Part-time positions are most uncommon for the non-clerical positions: heavy truck and lorry drivers, assemblers not elsewhere classified and plumbers and pipe fitters.

Annex Figure 1.A.4. Top 10 fast-growing Medium-Skill occupations – Offered Contract Characteristics



Note: NAs constitute 11% of the sample for type of contract and 24% for working hours.

Source: OECD calculations based on Lightcast data.

Low-skill occupations

Low-skilled occupations represent a share of about one third of the employed individuals in the Umbrian economy.¹⁷ Differently from the other two skill-levels, and as explored below, they face higher uncertainty in terms of stability of their jobs and higher competition, while at the same time having the lower barriers to entry. For these reasons they also represent an important target for the public employment service. The average benefit receiver is likely to have been laid-off or to seek training in occupations belonging to this category.

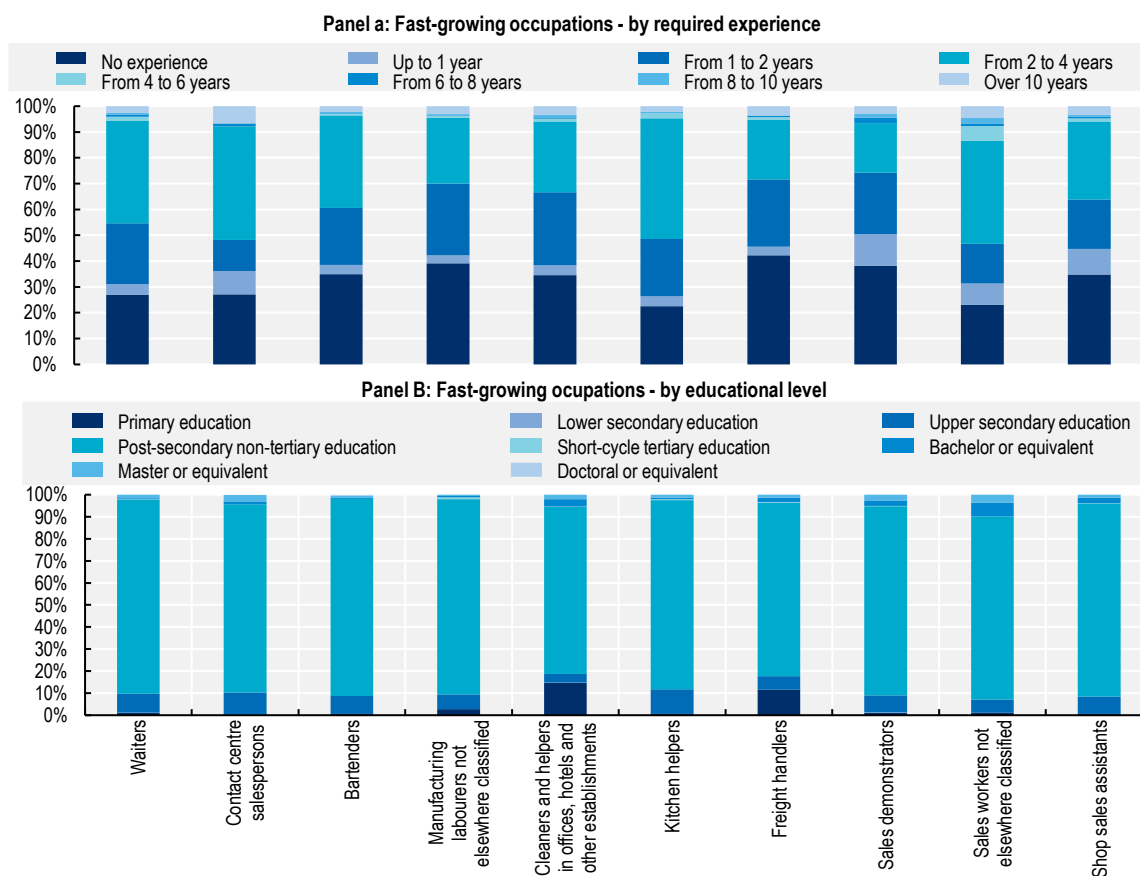
Three of the ten fast-growing low-skill occupations are part of the food industry, which contributes to volatility. The food industry is significantly affected by seasonality as was discussed previously, but at same time these occupations can provide opportunities to a large proportion of low-skilled unemployed people, given the total share of OJPs looking for food industry workers and the fact that is one of the areas where OJPs are fastest-growing.

However, there are more barriers to entry for food industry jobs than might originally be thought for a low-skill category. Annex Figure 1.A.5 shows that the required level of experience is a non-negligible requirement. Furthermore, the education level required is also quite similar to that of medium-skill occupations, with the vast majority of OJPs asking for post-secondary non-tertiary education. The underlying skills needed to perform food industry jobs are, however, not necessarily learned in school, but on the job. Panel A of Annex Figure 1.A.5 in fact, shows how from 50 to 60% of the vacancies associated with Waiters, Bartenders and Kitchen helpers still require from 2 to 4 years of experience and only about 20% to No experience.

Another fast-growing occupational area that in fact does have lower barriers to entry is sales. To this subgroup belong Contact centre salespersons, Sales demonstrators, Sales workers not elsewhere classified and Shop sales assistants. As shown in Annex Figure 1.A.5, Panel A, with the exception of Sales workers not elsewhere classified, OJPs for these positions are looking for candidates with less than 1 year of experience nearly 50% of the time, while the remaining half requires at least 2 years. Sales workers not elsewhere classified, however, often need to possess between 2 to 4 years of experience.

Cleaners and helpers in offices, hotels and other establishments, and freight handlers have the lowest barriers to entry both in terms of experience and in terms of education. Around 30% of vacancies are open to people without experience, and more than 10% of OJPs for these positions are open to people with only primary education.

Annex Figure 1.A.5. Top 10 fast-growing Low-Skill occupations – Expected Candidate Profile



Note: NAs constitute 60% of the sample for experience and 0.1% for education.

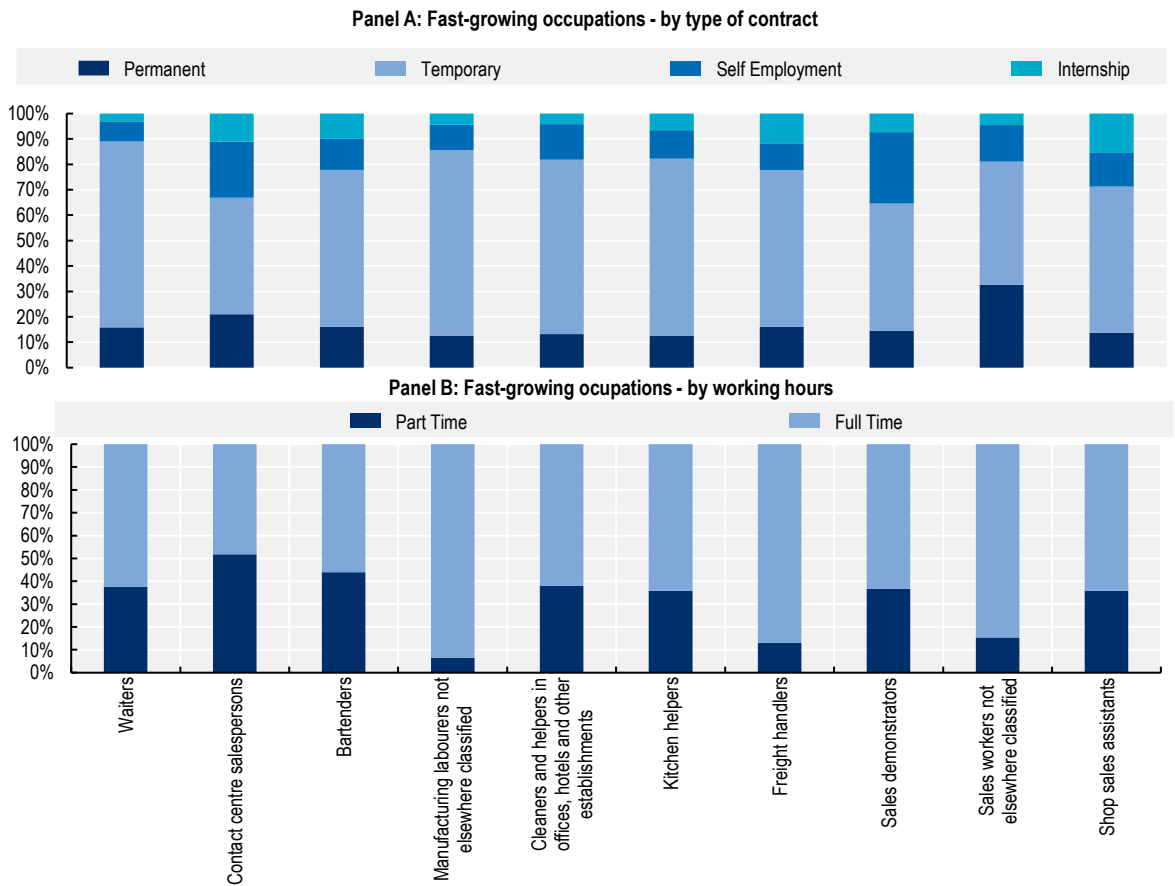
Source: OECD calculations based on Lightcast data.

Looking at the types of contracts that are offered to most of the fastest growing low-skill occupations, it stands out that between 10% and 20% of OJPs offer permanent contracts, which is lower than for the medium and high-skill occupations. Lower rates of permanent contracts contribute to lower job stability of low-skill occupations. One exception is the contract that is often offered to sales workers not elsewhere classified, as more than 30% of vacancies for this role offer permanent contracts.

Although sales workers not elsewhere classified often receive permanent contracts, there is also volatility for sales workers in general, as temporary contracts still dominate the type of contracts offered. Contact centre salesperson and Sales demonstrators trade-off roughly 20% of their share of temporary offers in favour of self-employment contracts. These positions along with shop sales assistants also receive part-time contracts in 40 to 50% of OJPs.

Part-time positions are much more prevalent for low-skill occupations, which can also contribute to volatility. Part-time contracts make up around 40% of OJPs for many of the food industry and sales positions (Annex Figure 1.A.6, Panel B). On the one hand, part-time contracts can offer flexibility to (young) workers to pursue for example education or fulfil other jobs. On the other hand, atypical part-time arrangements such as zero-hours contracts (*lavoro a chiamata o intermittente*) can lead to unpredictable working hours and earnings volatility (OECD, 2019^[24]).

Annex Figure 1.A.6. Top 10 fast-growing Low-Skill occupations – Offered Contract Characteristics



Note: NAs constitute 14% of the sample for type of contract and 22% for working hours.

Source: OECD calculations based on Lightcast data.

Notes

¹ Data used in this report come from Lightcast: <https://lightcast.io/>. More insights about the data can be found in Box 1.1.

² In the period under analysis, Umbria represents 1.06% of the total OJPs posted in Italy during the period and 7.1% of the online vacancies posted in the Centro macro-region.

³ The colour system included three tiers of anti-COVID measures, corresponding to the colours yellow, orange and red. Regions in Italy were assigned a colour based on an epidemiological assessment by the ministry. The anti-COVID measures included different levels of limitation to retail and service activities, limits to individual movement, curfews, and mandatory distance learning. (Manica et al., 2021^[25])

⁴ Eurostat calculations based on EU-LFS data. Sectorial classification is the NACE 2.0. Table code: LFST_R_LFE2EN2.

⁵ The high uncertainty in the period that immediately follows the pandemic makes particularly difficult to interpret labour market indicators. This applies to the period starting in January 2021, which shows a significant spike in monthly job postings in January 2021. One possible interpretation of it is that, as firms re-opened to economic activities, so did hiring, with a large number of vacancies that had been kept on hold until the announcement of the vaccination plan and that were instead published as the economy started to reopen.

⁶ High-skilled occupations group together the ISCO-08 1-digit codes 1, 2 and 3 where code 1 stands for *legislators, senior officials, and managers*, code 2 for *professionals* and code 3 for *technicians and associate professionals*. Medium-skilled occupations group together the ISCO-08 1-digit codes 4, 7 and 8 where code 4 stands for *clerks*, code 7 for *craft and related trades workers* and code 8 for *plant and machine operators and assemblers*. Low-skilled occupations group together the ISCO-08 1-digit code 5 for *service workers and shop and market sales workers* and code 9 for *elementary occupations*.

⁷ The OJPs in Umbria is characterised by a higher degree of volatility displaying a standard deviation of 139 vis-à-vis Italy standard deviation of 98 in Italy.

⁸ See: <https://www.arpalumbria.it/catalogo-regionale-dellofferta-formativa>.

⁹ Deriving insights from the lower end of the volume distribution requires an important caveat. There are two competing reasons why an occupation can be characterised by low demand: on the one hand an occupation can have a genuine low request from employers in the period and the market under analysis; on the other hand, for some occupations, online job boards might not be the most convenient channel to advertise a vacancy, creating selection in the sample.

¹⁰ The top 26 occupations at the 4th digit level represent, instead, 50% of total volume of OJP collected in Umbria. Similar representativeness is found in the metrics for Italy as a whole.

¹¹ In 2021 93% of the Italian population had access to the internet, and 10% of all purchases was made online (ITA, 2022^[26]).

¹² The increased demand for general office clerks is in line with the other trends that are observed for medium-skill jobs, and will be discussed in that section.

¹³ The requirements and task descriptions of secretaries and receptionists will be discussed in more detail in another subsection.

¹⁴ Both Freight handlers and Stock clerks are discussed in more detail in Chapter 3 of this report.

¹⁵ Contractual stability entails the type of contract someone receives: permanent, temporary, self-employment or internship.

¹⁶ While the tightness indicator for domestic, hotel and office cleaners and helpers increased in 2019 and 2020, it saw a slight decline in 2021. The indicator therefore remained smaller than average in 2021. The tightness indicator for shop sales persons was smaller than average in 2018, and continued to decline.

¹⁷ In the EU-LFS data 34% self-report in a High-skill occupation (code 1, 2, and 3 of the ISCO-08 classification at 1-digit), 37% in a medium-skilled (code 4, 7, and 8 of the ISCO-08 classification at 1-digit) and 29% in a low-skilled occupation (code 5, and 9 of the ISCO-08 classification at 1-digit). In the Lightcast data the share is 45% high-skill, 31% medium-skill and 24% low-skill.

2 The Regional Training Catalogue and its supply of training: A descriptive analysis

This chapter offers an overview of the courses provided in the Regional Training Catalogue (RTC) by the Umbrian regional agency for active labour policies (ARPAL). The analysis shows for which occupations training is available, and the corresponding number of training hours. Furthermore, leveraging Natural Language Processing (NLP) techniques, the chapter utilises algorithms and computational models to process and analyse the content of the courses described in the RTC in order to identify the skills that are provided in the training options available therein. Additionally, the chapter presents information on the cost, duration and class-sizes for the courses listed in the RTC, also highlighting the differences between the provinces of Perugia and Terni.

Highlights

- The Umbrian regional agency for active labour policies (ARPAL) provides training and education programs in the Regional Training Catalogue (RTC) to assist job seekers in the region. The RTC offers training for 81 different ISCO (International Standard Classification of Occupations) four-digit level occupations across low, medium, and high-skill levels and the programmes have varying time commitments and costs and cover a range of different topics, including technical and soft skills.
- Despite the RTC only targeting 11 low-skill occupations, 33.3% of all training hours are for low-skill jobs. The largest number of training hours is allocated to beauticians and related workers, followed by hairdressers and cooks. Training options targeting low-skilled occupations often have a longer duration than the other two skill-levels, which contributes to this result.
- The RTC focuses strongly on some medium-skilled occupations. Training courses for motor vehicle mechanics and repairers accounts for 13.8% of all medium-skill training hours and has by far the largest number of training courses that are currently offered (72 courses) across the whole RTC.
- When looking at high-skilled occupations, the RTC focuses intensely on training for ICT user support technicians, advertising and marketing professionals and web technicians, signalling that focus has been put on developing training opportunities for individual to train for digital occupations.
- Training cost is typically linked to the course duration. Among the most expensive courses are those for software developers (EUR 4 500), tailors, dressmakers, furriers and hatters (EUR 5 937), and beauticians and related workers (EUR 4 828). More inexpensive training courses are often shorter and are typically related to health and safety in the workplace (42%) or are refresher/update courses (38%).
- A large part of RTC training modules are aimed at developing skills potentially useful in a wide variety of job contexts such as “knowledge of contractual aspects in self-employed work”, and “evaluating the quality of service provision”. Results also show that five digital skills are among the most typically taught in the RTC but the share of individuals that could enroll in courses that explicitly teach these skills remains limited, as this ranges from 2.5% to 1.9% of the total available training spots.

The Umbrian regional agency for active labour policies (ARPAL) offers a range of training and education programmes to help people in the region find jobs in the Regional Training Catalogue¹ (RTC). These programmes cover various topics, from technical skills to soft skills, and have different time commitments and costs associated with them. A large part of the programmes is designed to prepare participants for specific occupations, and therefore, help them acquire the necessary skills and knowledge to enter or advance in the labour market.

It is worth noting that such training and education programmes are essential for supporting the development of a skilled workforce, which is a key driver of economic growth and social well-being. In many cases, individuals who lack the necessary skills to perform certain jobs are at a disadvantage when it comes to accessing employment opportunities. Through training programmes, these individuals can acquire the skills and knowledge they need to compete in the job market.

Moreover, the availability of training and education programmes is essential for employers too, as it helps them to find qualified candidates to fill their vacancies. By investing in the skill development of their employees, companies can also improve productivity and competitiveness, which ultimately contributes to the growth of the economy.

Table 2.1 shows the type of information that is available about each training in the catalogue, and specifically which variables are used for the analysis in this chapter and in Chapter 3.

Table 2.1. Information in the RTC

| Number | Variable name in Italian | Description | Number of observations/Missing values |
|--------|--------------------------|---|---------------------------------------|
| 1 | ID Progetto | Unique identifier of the education course | 1.649 unique IDs |
| 2 | Titolo Progetto | Title of the education course | Missing for 0% of training courses |
| 3 | Denominazione UFC | The “Learning Unit of Competence.” The variable contains a very short and general description of what is taught in each part of the course. | Missing for 0% of training courses |
| 4 | Denominazione UC | Competence Unit. This variable contains more detailed descriptions of what is taught in each part of the course. | Missing for 19% of training courses |
| 5 | ISTAT Profilo | ISTAT profile related to the education course. | Missing for 36% of training courses |
| 6 | Numero max Destinatari | The maximum number of students that can attend the course | Missing for 7% of training courses |
| 7 | Costo | Cost per participant for the entire course | Missing for 7% of training courses |
| 8 | Durata UFC | Duration of each entire course | Missing for 0% of training courses |
| 9 | Sede provincial sigla | Whether the training is offered in the region Perugia (PG) or Terni (TR) | Missing for 0% of training courses |

Source: OECD calculations based on information provided by ARPAL Umbria.

Three of these variables will be explained in further detail, to show how they are used, and what kind of information can be learned from them: ISTAT Profilo, Learning Unit of Competence, and Competence Unit.

Each training programme targets a specific profession, classified using the ISTAT (2021^[1]) occupational taxonomy. ISTAT created the *classificazione delle professioni CP2021* specifically for the Italian labour market, and the classification therefore does not correspond one-to-one to the ISCO classification that was used in Chapter 1. However, (Giabelli et al., 2022^[2]) have provided a framework on how to properly align the ISTAT classification with the ESCO/ISCO occupation taxonomy. Their mapping has been used in this report.

It is important to note that the majority of training programmes in the RTC is assigned to a specific ISTAT profile which represents the occupation of reference for which the content of the training has been developed. The association of each course to a ‘destination’ occupation is done to support beneficiaries in their decisions relative to what course to follow and for the PES, to track the skill area related to the training programmes from a statistical point of view.

It is also worth noting that the content of a course can be valuable for multiple job roles, even if it is only associated with one specific ISTAT occupation profile. For example, a course aimed at project managers can be classified into the ISTAT code 3.3.1.1.1 for “segretari amministrativi e tecnici degli affari generali” (administrative and technical secretaries of general affairs), but the content of this course could be valuable for project managers in both the public and private sectors. The fact that courses are classified in only one ISTAT occupation profile can affect some of the statistics in this chapter. For instance, the statistics on the training offer at the occupation level may be biased downwards as each course, despite being potentially useful for multiple occupations, is only associated with one ISTAT profile in the database of the RTC.²

All ISTAT codes have been mapped onto ISCO four digit level occupations for the purpose of the analysis in this chapter and consistency with the rest of the report that uses ISCO as the primary occupational taxonomy. This mapping, however, results in some loss of granularity in cases. For example, training courses for the ISTAT-occupations of coach builders (Carrozzeri), tyre fitters (Gommisti) and motor mechanics and motor vehicle repairers (Meccanici motoristi e riparatori di veicoli a motore) are all captured under the same ISCO four-digit occupation of motor vehicle mechanics and repairers, while the separate Italian ISTAT profiles show more nuance.

It is also interesting to notice that a large share of courses (36%) does not report targeting any specific occupation. One of the reasons behind this result is that most of those training opportunities are actually generic courses, which are for example related to health and safety in the workplace (see Box 2.1). These types of training can be followed by people in many different roles.

Box 2.1. The training offer for safety in the workplace: The Italian case

Italian employers have a legal obligation to ensure the safety of their employees. This obligation takes the form of for example mandatory surveillance of their employees' health, performing written risk assessments, making arrangements for first-aid care. Furthermore, employers are responsible for providing their employees with training and information on risks and health and safety (ILO, 2015^[3]).

The emphasis on workplace safety in Italy has led to a widespread prevalence of related training programmes. For instance, 26% of funds from the Interprofessional Fund (Fondi Interprofessionali) are devoted to training in this field. Moreover, the largest interprofessional fund, Fondimpresa, shows that 49.4% of the instances where a worker was enrolled in a training program, it was focused on workplace safety (OECD, 2017^[4]).

Examples of topics that are covered in RTC courses on health and safety that target low risk companies are: the concepts of risk, damage, prevention, and protection, and the rights, duties, and sanctions for different corporate subjects. Besides these conceptual topics, more concrete issues such as escape and fire procedures, or how to deal with manual handling of goods are part of the course guides of the RTC as well (ARPAL Umbria, 2022^[5]).

Two variables are especially important for the analysis in this chapter: i) Titolo segment UFC (i.e. the title of the learning goal) and ii) Competence Unit (i.e. the description of the skills and objectives of the learning module). These variables describe the learning objectives and the content of any given course, including the various skills that are taught and students are expected to master at the end of the course. The analysis of the keywords in these two variables makes it possible to determine the focus of each course. An example of the kind of information contained in these two variables is in Figure 2.1.

Figure 2.1 provides an example of the information available for a course designed for aspiring “web designers”. The course consists of 220 hours, divided into smaller learning units focused on specific topics. Unit five, for instance, is a 38-hour training on “web editing”, as indicated by the UFC. The UC provides more detailed information about the learning unit, specifying that it covers organizing web page content, implementing web editing techniques, and testing the website.

Figure 2.1. Example of the Learning Unit of Competence and the Competence Unit

| SEZIONE D | | | | | |
|--------------------------------------|---|---|-----------|--------------|-----------------------|
| ARTICOLAZIONE DELL'OFFERTA FORMATIVA | | | | | |
| D.1 Articolazione del percorso | | | | | |
| Numero segmento/ UFC | Titolo Segmento/UFC | Denominazione della UC di riferimento | Costo UFC | Durata (ore) | di cui erogate in Fad |
| 1 | Segmento di accoglienza e messa a livello | | | 2:00 | |
| 2 | UFC 1. "Esercizio di un'attività lavorativa in forma dipendente o autonoma" | UC.1 "Esercitare un'attività lavorativa in forma dipendente o autonoma" | | 6:00 | |
| 3 | UFC 2. "L'attività professionale di Web designer" | UC.2 "Gestire l'attività professionale di web designer" | | 8:00 | |
| 4 | UFC 3. "Definizione delle caratteristiche del web" | UC.3 "Analizzare le esigenze del cliente e supportare la definizione delle caratteristiche del web" | | 16:00 | |
| 5 | UFC 4. "Negoziazione e gestione delle relazioni tecniche e di servizio con il sistema cliente" | UC.4 "Negoziare e gestire le relazioni con il sistema cliente" | | 8:00 | |
| 6 | UFC 5. "Web editing" | UC.5 "Organizzare i contenuti delle pagine, realizzare il web editing e testare il sito" | | 38:00 | |
| 7 | UFC 6. "Elaborazione di immagini statiche" | UC.6 "Elaborare immagini statiche" | | 18:00 | |
| 8 | UFC 7. "Animazione 2D" | UC.7 "Creare animazioni 2D" | | 24:00 | |
| 9 | UFC 8. "Multimedialità nel web" | UC.8 "Elaborare ed integrare con tenuti multimediali" | | 36:00 | |
| 10 | UFC 9. "Elementi di programmazione web" | UC.9 "Realizzare semplici funzioni ed applicazioni web" | | 40:00 | |
| 11 | UFC 10. "Gestione delle risorse informatiche" | UC.10 "Gestire le risorse informatiche impiegate per le attività di web design" | | 8:00 | |
| 12 | UFC 11. "Sicurezza sul luogo di lavoro" | UC.11 "Lavorare in sicurezza in ambiente d'ufficio" | | 8:00 | |
| 13 | UFC 12. "La valutazione della qualità del proprio operato nell'ambito dell'erogazione del servizio" | UC.12 "Valutare la qualità del proprio operato nell'ambito dell'erogazione di un servizio" | | 8:00 | |
| Totale durata del percorso | | | | 220:00 | 0:00 |

Source: Data by ARPAL Umbria.

What kinds of jobs and skills are the focus of the RTC?

The occupations for which training is available in the RTC

The RTC offers training for 81 different ISCO four-digit level occupations across low, medium, and high-skill levels. This wide range of training opportunities covers various occupations of different complexities and natures.

To determine the focus of the RTC's training catalogue, the total number of training programmes offered at the occupation level has been multiplied by the duration of each training and the number of possible participants. This calculation provides the total number of training hours in each occupation, and it is a proxy of the intensity of the training supply by the RTC in Umbria.

Results in Figure 2.2 (panel A), show the top 40 occupations ranked by the total number of training hours. The data reveals that the focus of the training in the RTC is skewed towards beauticians and related workers, who receive 1.8 times more training hours than the second-most trained occupation (hairdressers).

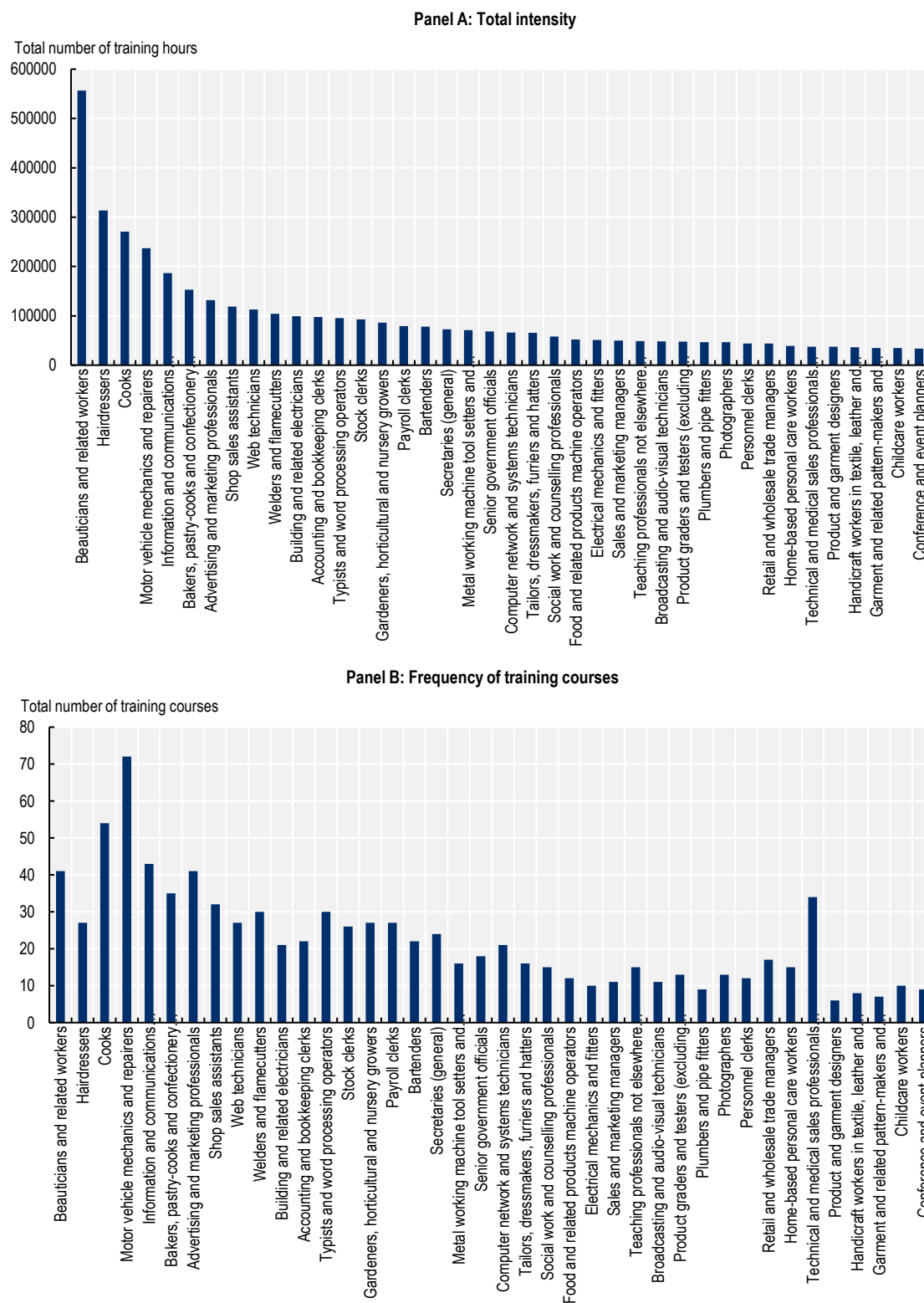
In comparison to beauticians, the number hours of training for the rest of the top-5 occupations, (hairdressers, cooks, motor vehicle mechanics and repairers, and information and communications technology user support technicians), are much lower.³

It is worth noting that the distribution of the number of training courses offered for each of the top 40 occupations is quite different from the distribution of training hours, as shown in Figure 2.2, panel B. Results show that the most frequent courses offered by ARPAL are for prospective motor vehicle mechanics and repairers, followed by courses for cooks. Courses for beauticians and related workers are only the fourth most frequent, despite receiving the highest number of training hours.

While the number of training hours for beauticians and related workers in Figure 2.2, panel A is significantly larger than for any of the other occupations, there are still a non-negligible number of training hours for the occupations ranking 35th to 40th in terms of intensity. The number of training hours available ranges from 34 000 for conference and event planners to 37 500 for technical and medical sales professionals (excluding ICT).

The data shows that the number of training courses offered for technical and medical sales professionals (excluding ICT) is relatively high, with a count of 34, although it ranks 35th on the list. Surprisingly, this number is almost the same as the count for courses taught to bakers, pastrycooks, and confectionery makers, which has a count of 35 and ranks 6th in terms of the RTC's focus. This suggests that the courses for medical sales professionals (excluding ICT) are either relatively short or have limited availability to participants.

Figure 2.2. Top 40 occupations on which courses in the RTC are focused



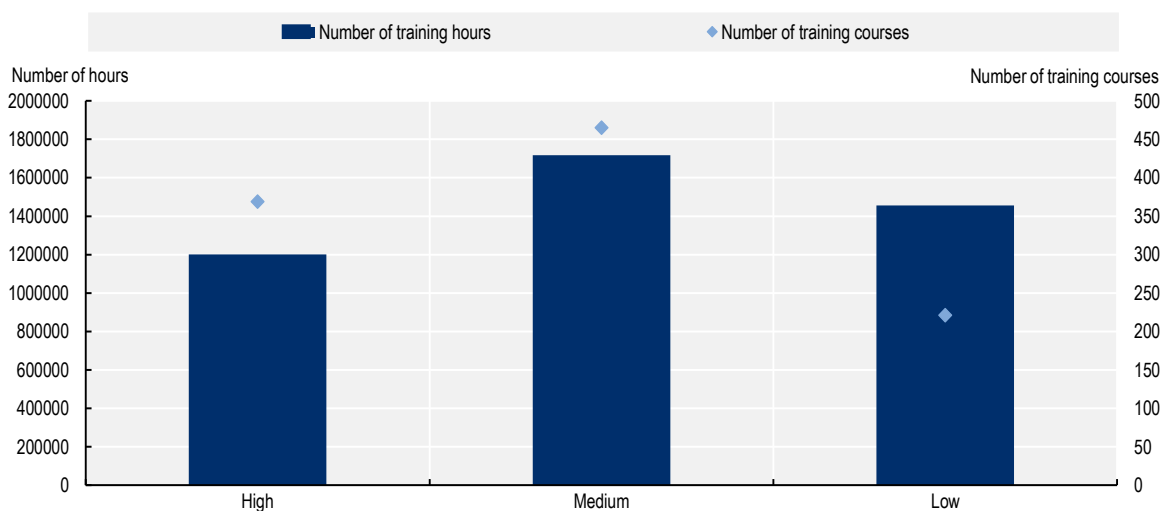
Note: Data on the RTC uses ISTAT to classify occupations, data in this graph is instead presented at the four-digit ISCO-level. One occupation in ISCO can encompass multiple ISTAT occupations. If that is the case duration and frequency for all ISTAT occupations have been added together.

Source: OECD calculations on data by ARPAL Umbria.

Data on the RTC indicates that, out of 81 occupations targeted, there is a wide variety of profiles and skill levels. While it is true that the proportion of courses offered for low-skill occupations is lower than for medium- and high-skill occupations,⁴ it is important to note that this does not necessarily mean that low-skill occupations receive the least amount of attention in the RTC. The total number of training hours available for low-skill occupations is still significant, even in a context where the number of training courses is smaller. When analysing the total number of training hours, results show that low-skill occupations receive a comparable amount of attention as medium-skill occupations. Figure 2.3 shows, for instance, that while the majority of training hours is still available to medium-skill occupations (39.3%), there are more training hours for low-skill occupations (33.3%) than for high-skill occupations (27.5%), emphasising the attention paid to low skilled workers in the total amount of training made available in the RTC.

The next sections go into more detail about the differences between the three different occupational skill-levels and explore the occupations for which the largest number of training hours is currently available in the RTC.

Figure 2.3. Number of training courses and intensity per occupational skill level



Source: OECD calculations on data by ARPAL Umbria.

The courses that are available in the RTC to train for a high-skill profession

The RTC provides a significant number of training options for student to learn skills related to several high-skill occupations, particularly those in information and communications technology (ICT) user support, advertising and marketing, and web development.

These three occupations concentrate a much larger number of total training hours than any other high-skill occupation listed in Table 2.2. The total number of training hours available to train as ICT user support technicians is particularly noteworthy, as it is around five times larger than the average number of available training hours for high-skill occupations. Moreover, there are almost four times as many training programmes available for ICT user support technicians relative to the average high-skill occupation.

It should be noted that ICT user support technicians comprise two different ISTAT occupations, including application engineers (Tecnici esperti in applicazioni) and programmer engineers (Tecnici programmatori). It is important to highlight that the training programs for application engineers within this one ISCO occupation exceed twice as many training hours compared to those for programmer engineers. While each

course is associated with only one ISTAT occupation of destination, the course content could be beneficial for multiple roles, despite being classified under only one specific ISTAT occupation profile.

The focus of the RTC on digital jobs is reflective of the increasing importance of digital skills in today's labour market, as mentioned in Chapter 1. With the rapid pace of technological change, workers need to constantly upgrade their skills to keep pace with new developments. ICT user support technicians, web technicians, and computer network and systems engineers are all highly in demand, and the fact that they receive a significant proportion of training hours indicates that the RTC recognizes this trend.⁵

In addition to these digital jobs, the RTC also places emphasis on management careers. Senior government officials and sales and marketing managers are both highly valued positions in their respective sectors, and the fact that they receive above-average training hours and number of training courses indicates their importance. These two management careers jointly make up 9.8% of all available training hours to train in high-skilled occupations. It is worth noting, however, that the number of training hours for government officials is significantly higher than that for sales and marketing managers, suggesting a greater availability of potential training for roles in the public sector.

Table 2.2. Top 10 high-skill occupations with the largest availability of training hours and courses in the RTC

| ISCO code | Occupation | Total training hours | Number of training courses |
|-----------|--|----------------------|----------------------------|
| 3512 | Information and communications technology user support technicians | 186525 | 43 |
| 2431 | Advertising and marketing professionals | 131626 | 41 |
| 3514 | Web technicians | 112725 | 27 |
| 1112 | Senior government officials | 68100 | 18 |
| 3513 | Computer network and systems technicians | 66370 | 21 |
| 2635 | Social work and counselling professionals | 57987 | 15 |
| 1221 | Sales and marketing managers | 49800 | 11 |
| 2359 | Teaching professionals not elsewhere classified | 48570 | 15 |
| 3521 | Broadcasting and audio-visual technicians | 48060 | 11 |
| 3431 | Photographers | 46530 | 13 |

Note: Data on the RTC uses ISTAT to classify occupations, data in this graph is instead presented at the four-digit ISCO-level. One occupation in ISCO can encompass multiple ISTAT occupations, as is the case for ISCO 3512 and 3521. For these occupations duration and frequency of the different ISTAT occupations have been added together.

Source: OECD calculations based on data by ARPAL Umbria.

The courses that are available in the RTC to train for a medium-skill profession

When analysing the training offer available to train in medium skilled professions, data on the RTC shows a significant focus on jobs such as motor vehicle mechanics and repairers, which alone make up 13.8% of all medium-skill training hours (as shown in Table 1.3). In addition, the RTC offers a significantly higher number of training courses in this area, with 72 courses available, which is 5.4 times higher than the average number of training courses offered for medium-skill jobs.

As mentioned previously, there are three different ISTAT occupations that jointly represent motor vehicle mechanics and repairers. Looking at these individual ISTAT occupations, by far the largest number of hours and number of training courses is targeting the generalist category of motor mechanics and motor vehicle repairers (*Meccanici motoristi e riparatori di veicoli a motore*), while the more specific subsets of coach builders (*Carrozzeri*) and tyre fitters (*Gommisti*) have fewer courses and training hours.

On the other hand, different roles such as clerical jobs are also well represented among the top 10 occupations by training intensity. Accounting and bookkeeping clerks, typist and word processing

operators, stock clerks, payroll clerks and secretaries (general) jointly receive 25.5% of the total training hours available for medium-skill jobs. The number of training hours for each of these occupations is also in between 1.4 and 2 times larger than average for medium-skill jobs. As discussed in Chapter 1, some clerical jobs require advanced administrative tasks (accounting and bookkeeping clerks, stock clerks, payroll clerks), while other require completing less sophisticated procedures (typist and word processing operators and secretaries (general)). However, the number of training hours available for each of the clerical roles, does not seem to depend on the sophistication of the tasks the clerical roles need to perform.

Table 2.3. Top 10 medium-skill occupations with the largest available training offer in the RTC

| ISCO code | Occupation | Total training hours | Number of training courses |
|-----------|---|----------------------|----------------------------|
| 7231 | Motor vehicle mechanics and repairers | 237200 | 72 |
| 7512 | Bakers, pastry-cooks and confectionery makers | 152940 | 35 |
| 7212 | Welders and flamecutters | 103890 | 30 |
| 7411 | Building and related electricians | 99000 | 21 |
| 4311 | Accounting and bookkeeping clerks | 97365 | 22 |
| 4131 | Typists and word processing operators | 95640 | 30 |
| 4321 | Stock clerks | 92655 | 26 |
| 6113 | Gardeners, horticultural and nursery growers | 86451 | 27 |
| 4313 | Payroll clerks | 79200 | 27 |
| 4120 | Secretaries (general) | 72615 | 24 |

Note: Data on the RTC uses ISTAT to classify occupations, data in this graph is instead presented at the four-digit ISCO-level. One occupation in ISCO can encompass multiple ISTAT occupations, as is the case for ISCO 7231, 7512, 7212, 7411, and 4321. For these occupations duration and frequency of the different ISTAT occupations have been added together.

Source: OECD calculations based on data by ARPAL Umbria.

The courses that are available in the RTC to train for a low-skill profession

The RTC only offers courses for eleven different low-skill occupations in total (see Table 2.4).⁶ Despite the low number of different occupations, 33.3% of all training hours is available to train towards a low-skill job, as courses in for those professions show a much larger number of total training hours. The average number of total training hours per low-skill occupation is 132 423, whereas it was 49 071 for medium-skill jobs and 34 320 for high-skill jobs. In terms of the training frequency as well, each low-skill occupation in the RTC has on average 20.1 training courses allocated to it, while it was 13.3 and 10.5 for medium- and high-skill jobs respectively.

The top three low-skill occupations in Table 2.4 are also those for which the availability of training is the largest in the whole RTC. Among these occupations, beauticians and related workers have the highest number of training hours, which is significantly higher than the average. In fact, the training hours dedicated to this occupation represent 38.2% of all low-skill training hours and 12.3% of all training hours in general. Analysis presented later in the section on training duration discusses the fact that training programmes for beauticians and related workers are relatively long.

Besides the focus on beauticians and hairdressers, training for food industry jobs also receives a significant focus. Courses for cooks, bartenders and waiters amount to a share of 25.5% of all training hours for low-skill jobs, an of 8.5% of all training hours in general.⁷ Restaurant cooks and waiters receive more training hours than their counterparts that work in other establishments.

Table 2.4. Focus for low-skill occupations in the RTC

| ISCO code | Occupation | Total training hours | Number of training courses |
|-----------|----------------------------------|----------------------|----------------------------|
| 5142 | Beauticians and related workers | 556650 | 41 |
| 5141 | Hairdressers | 313590 | 27 |
| 5120 | Cooks | 270555 | 54 |
| 5223 | Shop sales assistants | 118620 | 32 |
| 5132 | Bartenders | 78315 | 22 |
| 5322 | Home-based personal care workers | 39015 | 15 |
| 5311 | Childcare workers | 34575 | 10 |
| 5131 | Waiters | 22410 | 7 |
| 5414 | Security guards | 16200 | 11 |

Note: Data on the RTC uses ISTAT to classify occupations, data in this graph is instead presented at the four-digit ISCO-level. One occupation in ISCO can encompass multiple ISTAT occupations, as is the case for ISCO 5120, 5131 and 5414. For these occupations duration and frequency of the different ISTAT occupations have been added together.

Source: OECD calculations based on data by ARPAL Umbria.

The skills typically offered by the training courses available in the RTC

The RTC courses are designed to impart specific skills to participants, which are outlined in the course description (Learning Unit of Competence and Competence Unit). This section presents descriptive statistics of the intensity with which training programmes in the RTC focus on delivering specific skills. It does so by using both the keywords found in the RTC (in the description of the course content made by training providers) as well as by mapping those to the keywords that are typically used by employers use in online job postings.⁸

The training offer in the RTC encompasses approximately 1 375 different skills. Figure 2.4 shows the most prevalent ones⁹ by presenting the percentage of all potential participants who could follow training courses in each specific skill.¹⁰ Results in Figure 2.4 show that 48.6% of potentially available training spots in the RTC provide training modules aimed at developing transversal skills such as “Esercitare un’attività lavorativa in forma dipendente o autonoma” (ref: Attività dipendente autonoma) that is knowledge set required to “to understand the contractual aspects of professional performance and to understand the obligations necessary for the proper exercise of a freelance or quasi-subordinate work contract¹¹”. This skill includes how to handle the bureaucratic aspects of being self-employed, a skill that any self-employed person will need.

Data also show that around 51.5% of all potential participants are exposed to training focusing on safety measures in the workplace as many courses typically also have a module on safety while other courses are completely devoted to this topic. In total that means that there is the potential for 12 181 people to be trained in subjects that relate to this topic.¹²

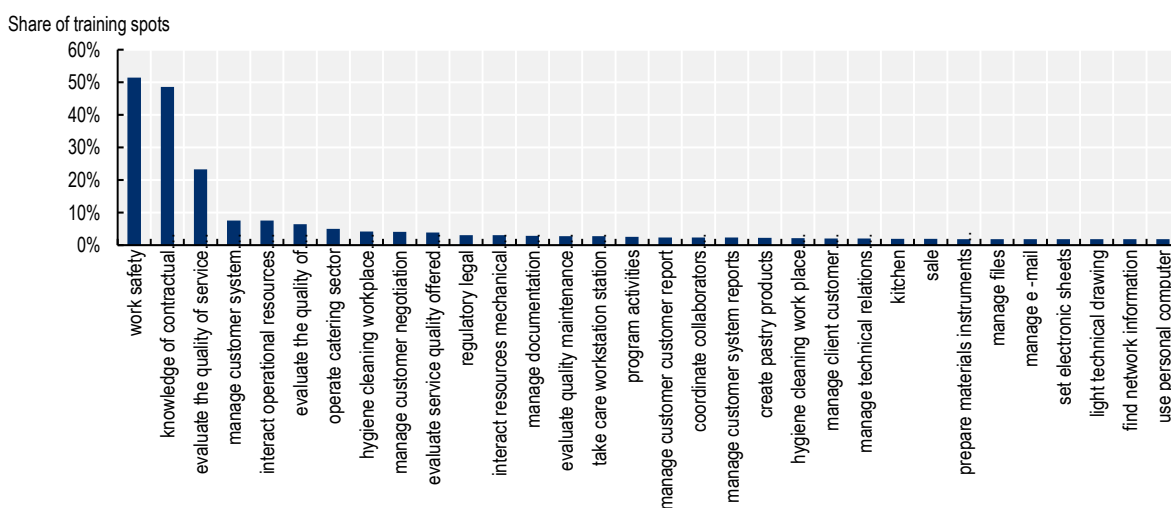
Results in Figure 1.4 also show that 23.3% of all potential participants in RTC courses are exposed to courses aimed at developing the necessary knowledge to “evaluate the quality of service provision”. Mastering this skill involves measuring performance, checking if there is anything that needs to be changed to provide a customer with a better experience. The principles of how to evaluate the quality of service will be similar between jobs, however, the specifics of the criteria on which to evaluate will differ.

Results also show that five digital skills are among the most typically taught in the RTC but the share of participants to whom learning options are made available on these digital skills remains lower than that of other skills. Programming activities, managing e-mail, creating electronic sheets, finding online information, and using a personal computer are all in the top 32 skills, but the shares of individuals that could learn them through one of the courses in the RTC ranges from 2.5% to 1.9%.¹³ 2.9% of training spots is available

for programming skills, this means that there are more training options for this skill than for more basic digital skills. However, basic digital skills are fundamental to build further knowledge, and while perhaps not many job postings will explicitly mention needing to be able to use an e-mailing service, it is often an implicit skill requirement.

Around half of the skills in Figure 2.4 are technical skills specific to a narrower set of occupations or industries. The shares of potential participants learning each of these technical skills vary. The technical skill that is taught to the largest share of potential participants is “evaluating the quality of manufacturing process”, which is taught to 6.4% of participants. The smallest share of participants in Figure 2.4 is learning about “light technical drawing”, at 1.9%.

Figure 2.4. The most prevalent skills taught to participants of the RTC courses



Source: OECD calculations based on data by ARPAL Umbria.

Mapping the skills in the RTC to the skills mentioned in OJPs

The language that employers use to describe skills in OJPs is typically different from that used by training providers to describe the learning goals of their programmes in the RTC. To assess the alignment between the skills taught in the RTC and the skills that are in high demand in Chapter 3, this section therefore first translates all the skills in the RTC to the language of the OJPs.

To achieve this goal, the skills as described in the RTC are mapped to the skills in the terminology of the Lightcast dataset. In global terms, an algorithm is used that looks at how similar an RTC skill is to all skills that are present in the Lightcast dataset. The algorithm is able to consider the entire context of the text in the online vacancies and in the course descriptions, to decide how similar two skills are, and it assigns a similarity score between them. More detail can be found in Box 2.2 and Annex A.

Box 2.2. Mapping skills in the RTC to skills in the terminology of Lightcast

Translating the skills from the RTC to the terminology of Lightcast necessitates recovering the semantic structure of how keywords (in this case skills) are used in the description of jobs vacancies and in those used to describe the content of training courses.

At the core of the machine learning technique used in this report lies the creation of the so-called word embedding. An embedding contains the coordinates and hence the position that each skill has in a high-dimensional vector space. These coordinates make it possible to assess how close or distant every pair of skills are from each other.

As each skill is represented by a vector, the distance between two skills A and B is a measure of vector distance given by the cosine of the angle between the two, the *cosine similarity*:

$$distance(A, B) = \frac{A \cdot B}{\|A\| \|B\|}$$

where the denominator expresses product between the L2-norm (or Euclidean distance) of each n-dimensional vector.

The main computational tool used for the embedding is fastText, which is an algorithm that is able to reach a numerical representation of words by means of a prediction task. fastText can focus on subwords: smaller portion of words. The idea behind the algorithm is to predict the presence of some subwords by the presence of those that surround it. The use of fastText on subwords, combined with the large amount of textual data coming from OJPs makes it possible to detect semantic meaning, which increases the accuracy of the translation.

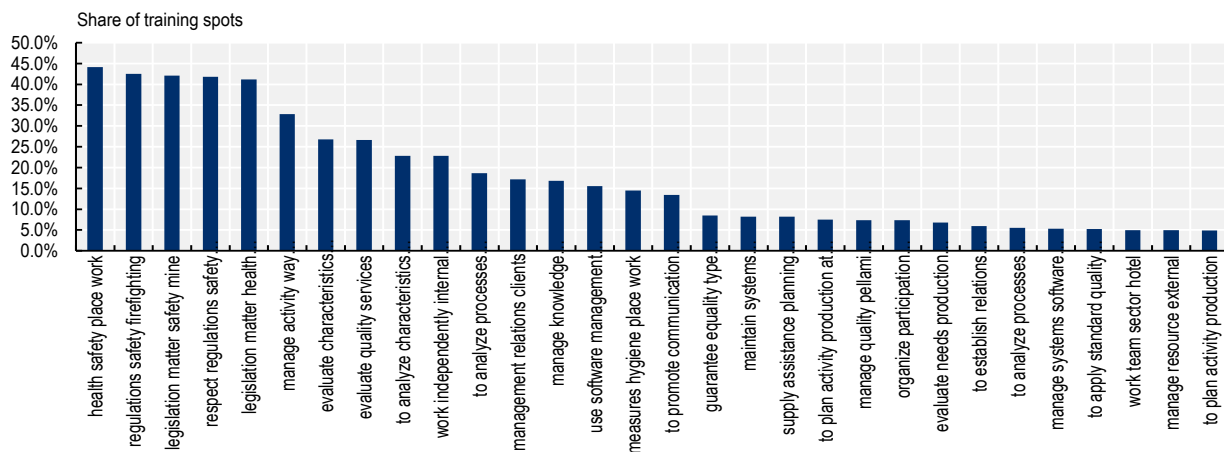
The skills in the RTC are paired with up to five skills that are extracted by Lightcast in OJPs. One RTC skill can be translated into multiple Lightcast skills as long as they are similar enough. The pairing is done between RTC and Lightcast skills that have a cosine similarity of at least 0.7, to ensure that the skills are indeed similar. For instance, the RTC skill “make_products_pastry” is linked to “prepare_products_pastry” which has a similarity of 0.91, but also to “make_products_pastry_base_chocolate”, which has a similarity of 0.85. According to fastText’s prediction, the skill “make_products_pastry” in the RTC is likely to also cover making chocolate pastry products, although the skills “make_products_pastry” and “make_products_pastry_base_chocolate”, are less similar than “make_products_pastry” and “prepare_products_pastry” are. Including both Lightcast skills as a proxy for the RTC skill “make_products_pastry” therefore gives more information on what a course that teaches “make_products_pastry” teaches, than just including one skill would do.

Note: More information on fastText, and on the process of mapping the skills can be found in Annex A.

Figure 2.5 shows the most prevalent 30 skills supplied in RTC training programmes by using the same terminology found in OJPs.¹⁴

After mapping the skill keywords used in the RTC into the language of OJPs, results remain qualitatively similar as expected. In particular, Figure 2.5 shows a similar picture to Figure 2.4. Nearly two thirds of the skills in the top 30 are skills are not specific to a specific industry or job, highlighting the varied nature of the training in the RTC. Results also highlight that some 41% to 44% of available training spots provides modules about health and safety in the workplace, regulations concerning safety in firefighting, and respecting safety regulations for example.

Figure 2.5. Top 30 skills in the terminology of Lightcast, weighted by similarity score

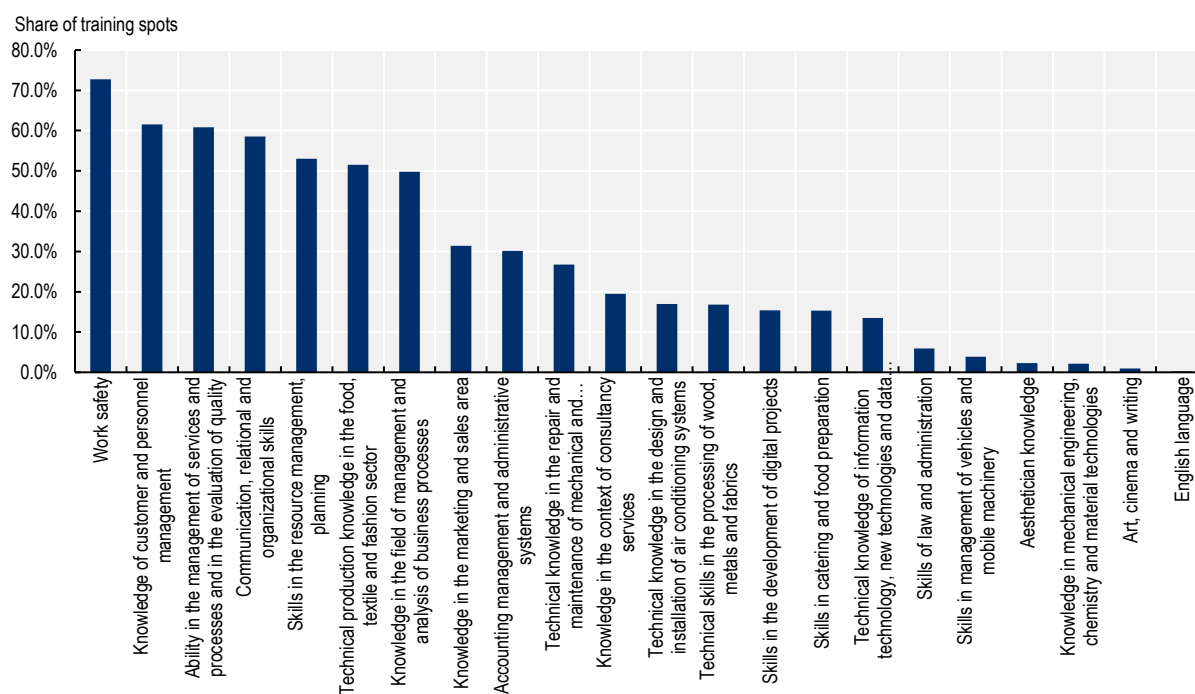


Source: OECD calculations based on Lightcast data and data by Arpal Umbria.

The RTC provides 1375 skills to its participants, and many of these skills are related to each other. To determine if certain topics receive more attention than others, a k-means algorithm¹⁵ was used to create clusters of similar skills. The results, shown in Figure 2.6, reveal, unsurprisingly, that the RTC places the most emphasis on teaching work safety. In addition to this, around 60% of participants also receive training in customer and personnel management, service and process management, quality evaluation, communication, relational and organizational skills. This translates to approximately 14,380 individuals learning skills in these areas. However, the training offered for English language proficiency is limited, as only 0.2% of participants receive training in this subject. Similarly, training for arts, cinema, and writing is provided to only around 1% of participants.

Interestingly, the prevalence of certain clusters with job-specific skills for jobs which are a focus of the RTC as shown in the previous subsection, is rather low. For example, the cluster that relates to knowledge for beauticians is only taught to 2.3% of participants. As was previously discussed, the occupation of beauticians and related workers was ranked fourth in terms of the number of training courses. The fact that the job-specific skills beauticians are only taught to a very limited share of participants, means many of the courses aimed at beauticians are focusing on transversal skills which are a part of other clusters. As the courses for beauticians were generally quite long, it is very likely that there are sub-parts of the courses, which are only focusing on workplace safety, or how to run a business for example.

Figure 2.6. Skill clusters weighted by similarity scores



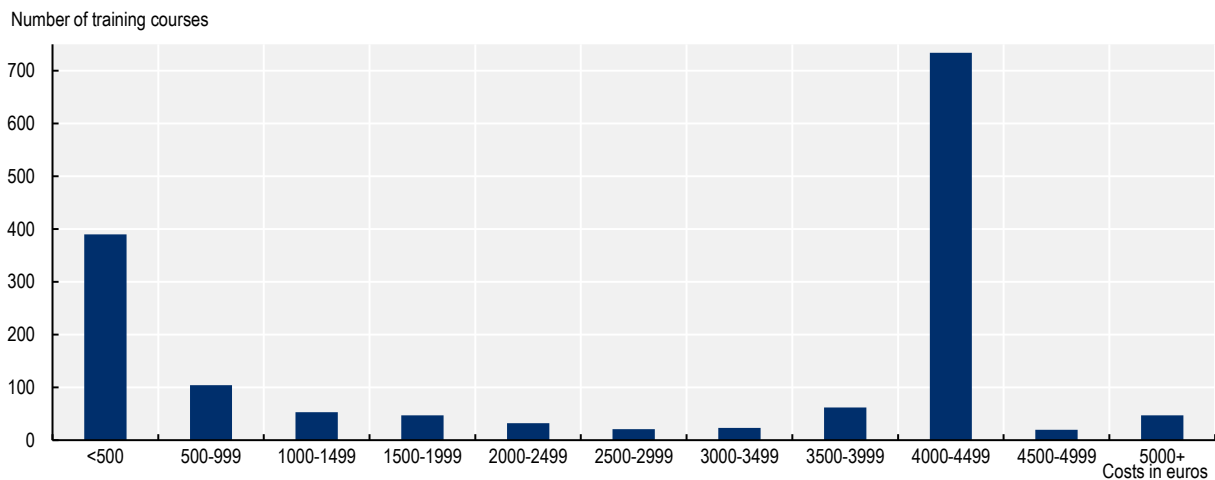
Source: OECD calculations based on data by ARPAL Umbria.

The cost and length of the training offer in the Regional Training Catalogue

Cost of training

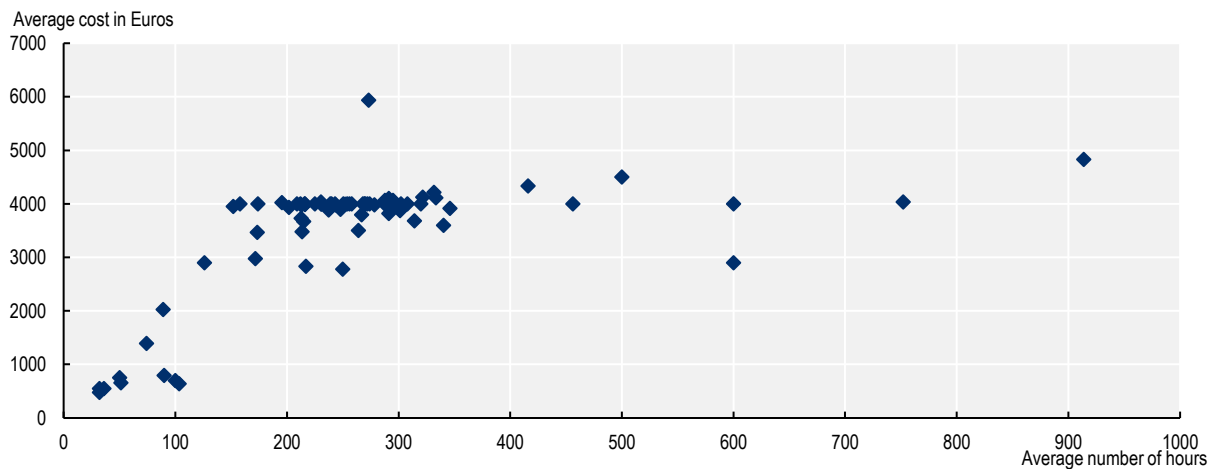
The overall cost associated with the training courses offered in the RTC ranges from inexpensive options of less than EUR 100 to expensive programmes of more than EUR 30 000 (Figure 2.7). A large share of training courses (725 out of 1 533), however, cost exactly EUR 4 000 (Figure 2.7). Among the potential reasons for this result is that several of those courses could be paid using “training vouchers” issued by the Italian government for the same amount. Several training options were hence created in such a way that they could use the full amount of the voucher.¹⁶

Figure 2.7. Frequencies of cost per training



Source: OECD calculations based on data by ARPAL Umbria.

Figure 2.8. Average cost per training against the average training duration



Source: OECD calculations based on data by ARPAL Umbria.

Unsurprisingly, more expensive courses are often also courses that have a longer average duration (Figure 2.8). Around 25% of courses cost less than EUR 500 (Figure 2.7), and these cheaper courses are usually not associated with a specific occupation. In fact, only 4.6% of these relatively cheap courses have an ISTAT occupation linked to it. The majority of cheaper courses are also relatively short. Some 403 training courses cost of less than EUR 400 their duration is of less than 20 hours. Table 2.5 shows an example of the kind of courses that meet these criteria.

A majority of the shorter and less expensive training courses concerns courses related to health and safety in the workplace. In fact, courses that mention health and safety, fire prevention, risk prevention or first aid are nearly 42% of the courses below EUR 400 that last less than 20 hours (see also Box 2.1).

Furthermore, a significant share of the shorter and less expensive courses are either refresher/update courses (38%) or training courses that teach how to operate heavy equipment (36%) and, in particular, training programmes focusing on learning how to operate heavy machinery like cranes and fork lifts, with nearly a third of those training courses being refresher courses. While many of these courses do not mention that they target a specific occupation, the skills that are taught are very specific and not easily transferable between many occupations. Skills to operate a self-propelled industrial forklift truck or a tracked agricultural tractor for example are most useful for positions as lifting truck operator (ISCO 8344) and mixed crop grower (ISCO 6114). However, because the training courses are quite short, the skills should be relatively easy to learn within a limited time frame, so transferability is not a big issue.

Table 2.5. Example of training courses that take fewer than 20 hours and cost less than EUR 400

| | Training name in Italian | Translation |
|----|---|--|
| 1 | Aggiornamento dei lavoratori in materia di salute e sicurezza | Update of workers on health and safety |
| 2 | Aggiornamento per addetti al pronto soccorso – aziende gruppo a | Update for first aid workers – companies of group a |
| 3 | Aggiornamento per lavoratori in materia di salute e sicurezza in riferimento all'accordo stato – regioni del 21.12.2011 | Update for workers on health and safety in reference to the state – regions agreement of 12.21.2011 |
| 4 | Aggiornamento teorico-pratico per lavoratori addetti alla conduzione di carrelli elevatori semoventi con conducente a bordo | Theoretical-practical update for workers involved in driving self-propelled forklift trucks with driver on board |
| 5 | Aggiornamento teorico-pratico per lavoratori addetti alla conduzione di piattaforme di lavoro mobili elevabili | Theoretical-practical update for workers involved in the operation of elevating mobile work platforms |
| 6 | Corso di formazione per i lavoratori in materia di salute e sicurezza nei luoghi di lavoro – rischio alto | Training course for workers on health and safety in the workplace – high risk |
| 7 | Corso di formazione teorico-pratica per lavoratori addetti alla conduzione di gru a rotazione sia in basso che in alto. | Theoretical-practical training course for workers involved in operating both low and high rotation cranes. |
| 8 | Corso di formazione teorico-pratico per addetti alla conduzione di gru per autocarro | Theoretical-practical training course for truck crane operators |
| 9 | Formazione per addetti alla prevenzione incendi, lotta antincendio e gestione delle emergenze. In rischio basso | Training for fire prevention, fire fighting and emergency management personnel. Low risk |
| 10 | Corso di formazione aggiuntiva per preposti. | Additional training course for supervisors. |

Source: Data from ARPAL Umbria.

On the other side of the cost distribution, it stands out that expensive courses are often courses that require internships or practical/hands on education or are training courses that provide a certain certification. They are also often longer courses, as mentioned before (Figure 2.8). Table 2.6 shows an example of the kinds of courses that are more than 200 hours and cost over EUR 800. There are 363 courses that meet these criteria, and 31% of them mention an internship or lab work as part of the curriculum. Besides that, 55% of these training courses mention that they lead to a certification, like qualified bar service employee, or that they educate someone to be able to fulfil an occupation that is specified in a certain law, like beautician – according to law 1/1990 article 3, see for instance Box 2.3. Government of Italy

Box 2.3. The skills and requirements for beauticians and related workers

Beauticians and related workers (*estetisti e truccatori*) “give clients facial and body beauty treatments, apply cosmetics and make-up and give other kinds of treatment to individuals in order to improve their appearance” (ISCO-08). To perform these tasks, they need to know for example how to give facial and body massages, how to best apply make-up to suit their clients’ needs, or for example how to wax or use depilation techniques to remove unwanted hairs.

The Italian law necessitates having a specific professional qualification, before being allowed to practice as a beautician. In 1990, the Italian government passed a law which describes all the tasks and requirements of beauticians (*estetista*) (Government of Italy, 1990^[6]). To obtain the professional qualification of beautician, someone needs to have passed an exam after following a course that lasts at least 900 hours, or they need to pass the exam after working as an apprentice for at least a year complemented by following at least 300 hours of training. The requirements within the law explain why so many of the courses for beauticians and related are relatively long and expensive, as well as why internships are quite common. In fact, most of the beautician courses in the RTC take around two years, which is longer than is required.

RTC Training to become a beautician costs on average EUR 4 828, and the training time is relatively long. The average yearly earnings of a beautician in Italy are around EUR 25 000 (ERI, 2022^[7]), which is slightly below the average wage of 29 694 in 2021 (OECD, 2023^[8]). Of course, there are more reasons why someone would want to perform a certain job, but the earnings potential of beauticians is slightly below average. Chapter 3 goes into more depth on how highly demanded beauticians are, which can influence how easy it will be to find a position as a beautician.

It is true that longer and more comprehensive training courses can provide better preparation for the labour market, as they often cover more extensive material and may require practical work experience through internships or apprenticeships. These types of programs are particularly useful for individuals who are seeking to enter new fields or industries, as they provide a more in-depth understanding of the specific skills and knowledge required for those roles. In addition, completing an accredited training program can be beneficial for obtaining a job. Accreditation provides official recognition of an individual’s skills and knowledge, which can improve their chances of being hired by potential employers. This is especially true in fields such as healthcare, where accreditation is often required in order to practice in certain roles.

However, it is important to note that longer training courses can also have some disadvantages, such as a delayed entrance into the labour market. This can be due to the additional time required to complete the training, as well as the potential need to complete additional practical experience or apprenticeships. In some cases, shorter training programs may be more appropriate for individuals who are looking to quickly acquire specific skills or enter the labour market more quickly. Ultimately, the decision of whether to pursue a longer or shorter training program depends on the individual’s specific career goals, financial situation, and availability of job opportunities in their field.

The topics or occupations that are covered by the longer and more expensive training courses are more varied than for the shorter and less expensive training courses. Notable career areas are jobs related to mechanics and engineering, which are around 18% of the longer and expensive courses, beauticians and hairdresser courses (13%), food industry jobs (16%), jobs related to craftsmanship or arts (9%), and clerical jobs (7%), and jobs as designers (6%). One of these craftsman jobs which has on average the most expensive courses for the medium-skill level, is the job tailor/dressmaker/furrier and hatter, more detail is provided in Box 2.4.

Table 2.6. Example of courses that take more than 200 hours and cost more than EUR 800

| | Training name in Italian | Translation |
|----|--|---|
| 1 | Estetista – specializzazione (600 ore) – legge 1/1990, art. 3, comma 1 lettera a) – abilitazione all'esercizio di attività autonoma | Beautician – specialization (600 hours) – law 1/1990, art. 3, paragraph 1 letter a) – authorization to practice self-employment |
| 2 | Acconciatore. Percorso di qualifica biennale | Hairdresser. Two-year qualification course |
| 3 | Cuoco | Cook |
| 4 | Addetto qualificato al servizio bar (percorso aula e stage) | Qualified bar service employee (classroom and internship) |
| 5 | Tecnico per l'attività di Gommista delle autoriparazioni | Tire repair technician |
| 6 | Tecnico per l'attività di carrozzeria delle autoriparazioni (percorso di aula e stage) ai sensi dell'art. 7, comma 2, lett. B) della legge 5 febbraio 1992, n.122 e s.m.i dell'accordo stato regioni del 12 luglio 2018 rep. Atti n. 124/csr | Technician for the bodywork activity of car repairs (classroom course and internship) pursuant to art. 7, paragraph 2, lett. B) of the law of 5 February 1992, n.122 and subsequent amendments of the state-regions agreement of 12 July 2018 rep. Deeds n. 124/csr |
| 7 | Addetto qualificato al confezionamento – capi abbigliamento e maglieria | Qualified garment maker – clothing and knitwear |
| 8 | Addetto qualificato al front office (percorso aula e stage) | Qualified front office employee (classroom path and internship) |
| 9 | Web designer (aula+stage) | Web designer (classroom+internship) |
| 10 | Disegnatore CAD (percorso aula e stage) | CAD designer (classroom path and internship) |

Source: Data from ARPAL Umbria

Box 2.4. Courses for tailors, dressmakers, furriers and hatters

Training for the ISCO occupation of tailors, dressmakers, furriers and hatters is made up of training courses for two different ISTAT occupations: garment makers (*Confezionatori di capi di abbigliamento*) and tailors (*Sarti*). The most expensive training courses are those that are particular to garment makers, which cost EUR 7 874 on average, as compared to EUR 4 000 for tailors. Garment makers take care of the areas of production that precede the finishing of the prototypes, they work on identifying the most suitable materials and small parts such as buttons and zippers, and they prepare garments for assembly by sewing machines. Garment makers cut and sew garments themselves as well. The garment maker should also be able inspect and perform quality control the produced product.

The courses for garment makers in the RTC aim to supply a variety of skills to students to enable them to understand the needs of companies and customers in the production of clothing and knitwear. The courses also aim to develop digital skills, such as the use of specialised software that helps the garment maker decide on the types of seams, the size table and washing methods and software that helps garment makers to create buttonholes, pockets, embroidery and other stylistic details that define the garments.

The job of a garment maker can be quite varied, with different types of garment makers earning different salaries. For instance, fashion designers on average earn EUR 55 000, while costume designers earn EUR 29 000 (ERI, 2022^[9]). On the other hand, garment sewers have an average wage of EUR 20 500. The average wage in Italy in 2021 was 29 694 (OECD, 2023^[8]). With salaries ranging from EUR 9 000 below average to EUR 25 000 above average, it is hard to say whether there is a lot of earnings potential in the role of garment maker, and whether such a large investment in the courses would pay off for every student.

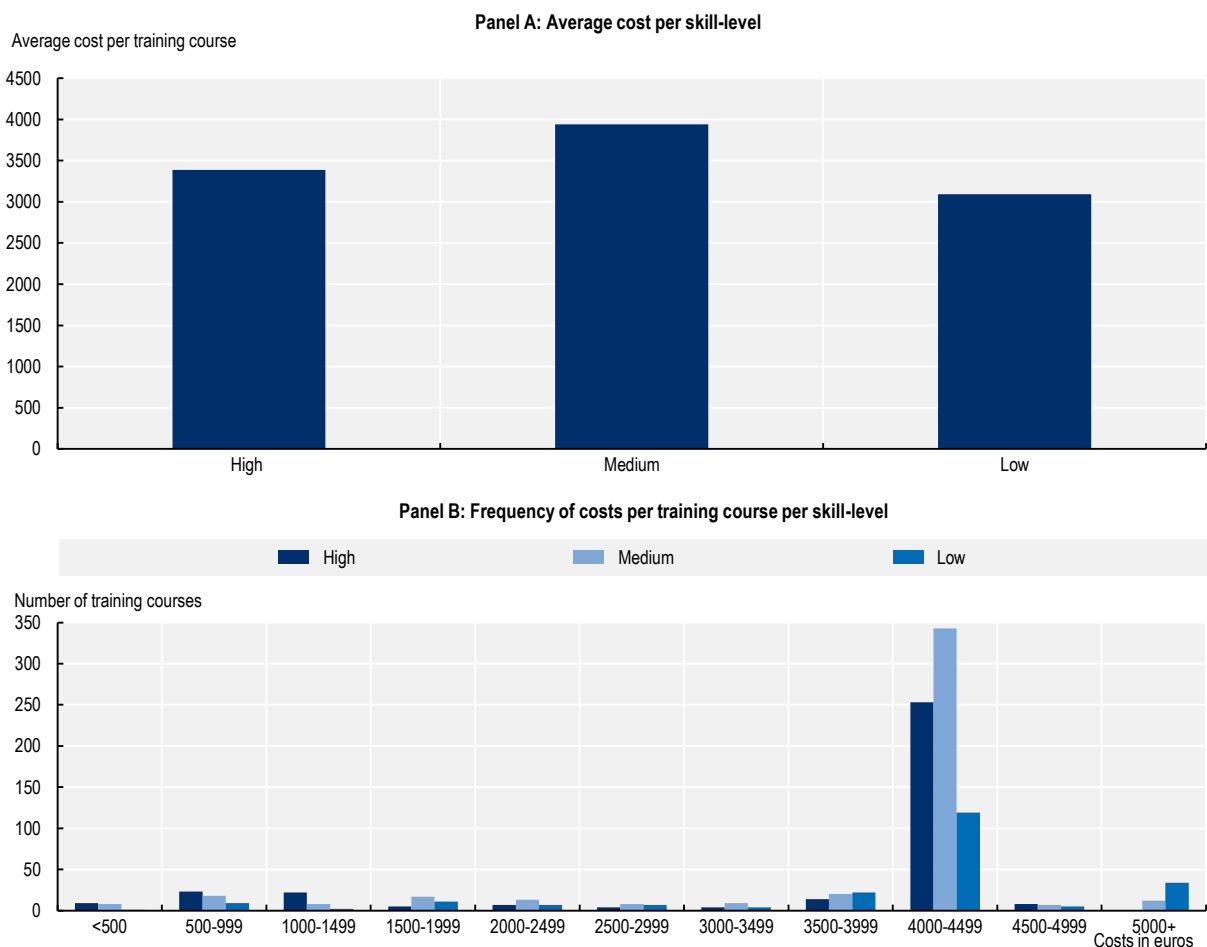
Differences in the average training cost (per worker) by high, medium and low skilled occupations are less than a EUR 1 000. On average, someone seeking training to perform a high-skill job would pay around EUR 3 400 to access training offered for their occupation, relative to EUR 3 940 in the case of a medium-skilled worker and EUR 3 100 for low-skilled jobs (see Figure 2.9, Panel A).

Nonetheless, the distribution of costs is quite different, especially looking at the least and most expensive courses (Figure 2.9, panel B). The least expensive courses are more prominent for high-skill occupations. The share of high-skill courses that costs less than EUR 500 is 2.6% versus 1.7% for medium-skill courses and only 0.5% for low-skill courses. Potentially, there are more courses aimed at high-skilled occupations that are shorter in terms of training hours, which could explain the difference in cost. The differences in duration per skill-level are explored in a later subsection.

While there are no training courses for high-skill occupations that cost over EUR 5 000, 2.6% of training courses for medium-skill occupations and even 15.4% of training courses for low-skill occupations come with such an expensive price tag. The low-skill and medium-skill jobs with the highest costs have been described in Box 2.3 and Box 2.4. The high-skill job with the highest average price is the role of software developer, this job is described in more detail in Box 2.5.

At the same time, courses that cost exactly EUR 4 000 are much more prominent for high-skill and medium-skill workers than for low-skilled workers. About 72% and 74% training courses for high- and medium-skilled occupations cost EUR 4 000, while only 52% of low-skilled courses costs the same. Potentially, more courses for medium- and high-skilled occupations were eligible for the use of a training voucher in the past.

Figure 2.9. Cost of training courses per occupational skill level



Source: OECD calculations based on data by ARPAL Umbria.

Box 2.5. The tasks, skills and earnings of a software developer

The most expensive courses for high-skill occupations are those targeting software developers (ISCO 2512). These courses cost on average EUR 4 500. Software developers (Analisti e progettisti di software in Italian) are responsible for researching and evaluating the requirements for existing or new software applications. They also design, develop, test, and maintain software solutions (ISCO-08).

The courses that are offered in Umbria are specifically for web designers. These professionals need to be able to tackle both the graphical design and the technical implementation of a website. It is therefore necessary to train mostly technical digital skills like the creation of 2D animations and the use of programming languages. But web designers also need to know how to target their customers' needs, how to monitor and operate the sites they developed and how to make sure that a site is in compliance with for example data security rules. In short, a wide variety of skills are needed to become a web designer.

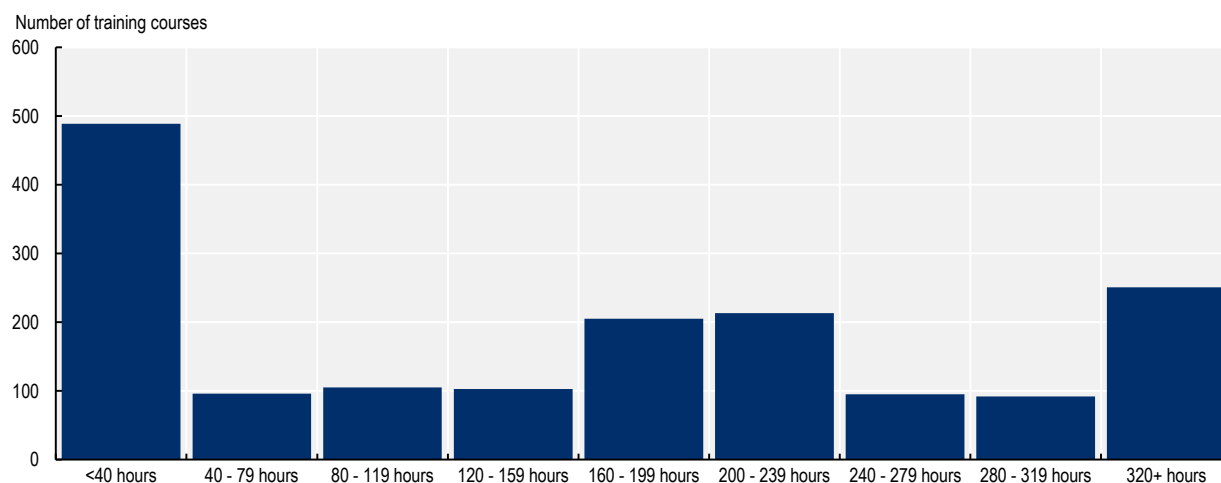
While the training courses to become a software developer are among the priciest training courses offered in the RTC, software developers also have a high earning potential. The average yearly salary for this position in Italy is reported to be EUR 63 459 (ERI, 2022^[10]), compared to the average salary of EUR 29 694 in 2021 (OECD, 2023^[8]).

Source: ISCO-08, Data from ARPAL-Umbria.

Duration

Like with the costs of the training courses, there is a wide range of training durations as well (Figure 2.10). The largest share of training courses (29.7%) takes less than 40 hours. At the same time 15.2% of training courses take more than 320 hours. The longest recorded duration is 1800 hours, which is equivalent to 45 workweeks. There are 13 training courses with a duration of 1 800 hours, mostly for training courses for cooks, and beauticians. The average length of a course is 187 hours, which is close to 4.5 weeks of training. Around a quarter of training courses take between 160 and 239 hours.

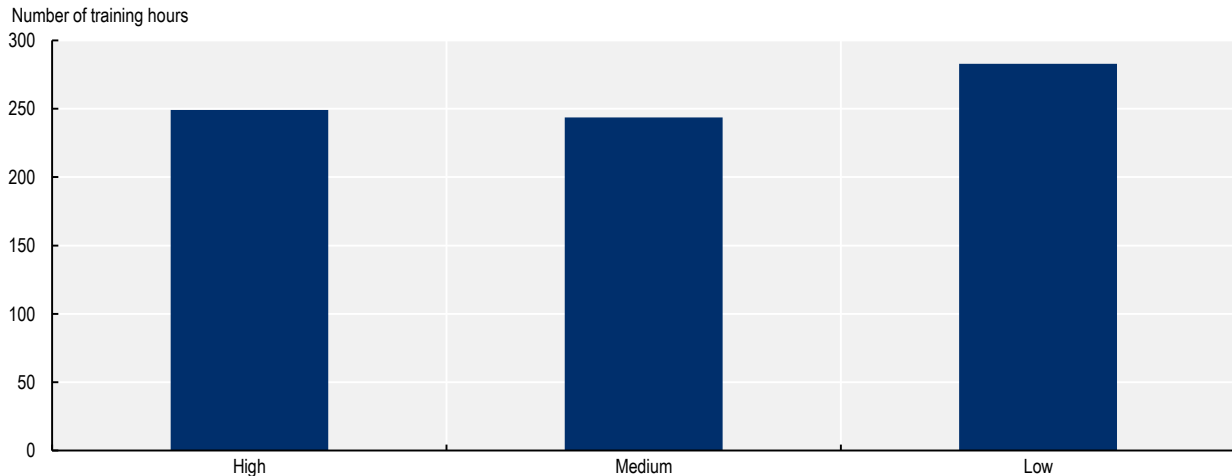
Figure 2.10. Frequencies of training duration



Source: OECD calculations based on data by ARPAL Umbria.

The data shows that training for low-skilled occupations tends to have a longer average duration compared to training for medium- and high-skilled occupations, as shown in Figure 2.11. On average, low-skilled occupation training lasts 39 hours longer than medium-skilled occupation training and 34 hours longer than high-skilled occupation training. However, it's important to note that the average costs for medium- and high-skilled occupations are actually larger than those for low-skilled occupations. This suggests that average training duration alone cannot fully explain the difference in training costs between the skill levels, although longer training programs do often come with higher costs. The relation between cost and training duration is explored in more depth for creative jobs in Box 2.6.

Figure 2.11. Average number of training hours per occupational skill level



Source: OECD calculations based on data from ARPAL Umbria

Box 2.6. The relation between cost and duration for creative jobs

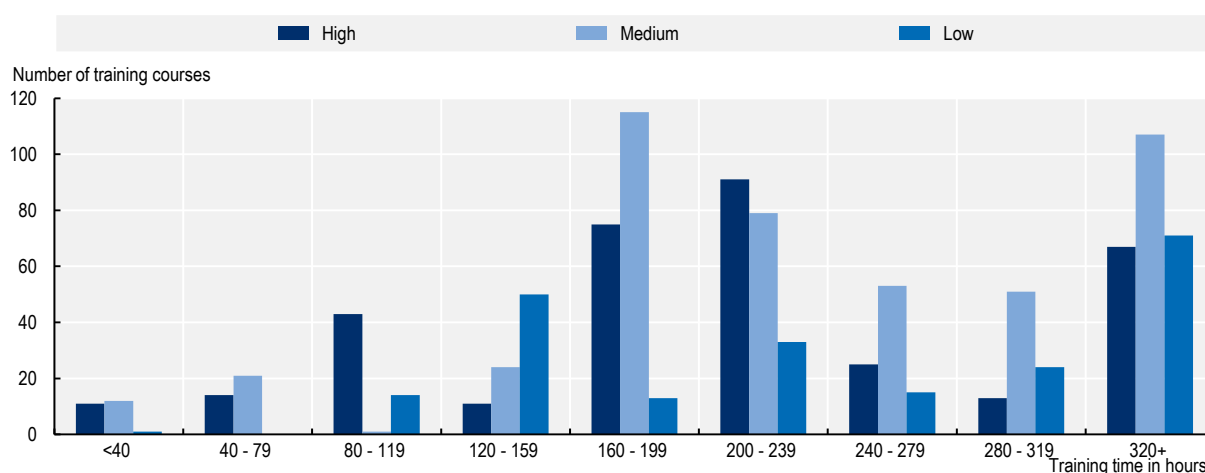
Training courses for creative jobs are generally among the most expensive training courses. For high-skilled occupations, product and garment designers, interior designers and decorators, photographers, graphic and multimedia designers and visual artists all have training courses of EUR 4 000 or more. For medium-skilled jobs, tailors, dressmakers, furriers and hatters; garment and related patternmakers and cutters; potters and related workers; jewellery and precious-metal workers, and wood treaters all have training courses that cost more than EUR 4 000 on average.

For some of these creative jobs, the high prices are accompanied by a generally large number of training hours. Following a course for garment and related patternmakers and cutters for example takes 332 training hours. Wood treaters also have training durations that are longer than average. Training courses for the high-skill jobs visual artists and product and garment designers are also in the top ten longest high-skill training courses.

However, for most of the high-skill creative jobs, and some of the medium-skill creative jobs, the training courses are not among the longest training courses. For example, the occupation with the most expensive training courses is tailors, dressmakers, furriers and hatters, which cost EUR 5 937. The number of training hours is 273 hours, which is even below average for medium-skilled jobs. Training courses for potters and related workers and jewellery and precious-metal workers also are shorter than average, while being expensive. Training for interior designers and decorators is even among the top ten shortest training courses for high-skilled jobs. Potentially, costs for materials and for software are increasing the prices for these training courses for jobs in the creative sector, instead of an increase of training hours.

Figure 2.12 provides further evidence that low-skilled occupations require longer training durations compared to high- and medium-skilled occupations. The figure displays the distribution of training durations across different skill levels, indicating that there are significantly more short training courses of less than 80 hours for high- and medium-skilled workers, while only 0.5% of low-skilled training courses fall in this category. Interestingly, the figure also shows that nearly one third of training courses for low-skilled occupations are over 320 hours, which is much higher than the corresponding percentages for medium- and high-skilled occupations. This suggests that longer training durations are indeed a common feature of training programs for low-skilled occupations, which may reflect more practical work and internships required for these jobs. Moreover, it is notable that the peak of the distribution for medium-skilled training courses is in the range of 160 to 199 hours, while for high-skilled training courses it is in the range of 200 to 239 hours. This may reflect the fact that medium-skilled occupations typically require a narrower range of specialized skills compared to high-skilled occupations, which may require more extensive training in a broader range of areas.

Figure 2.12. Frequencies of training duration by occupational skill level

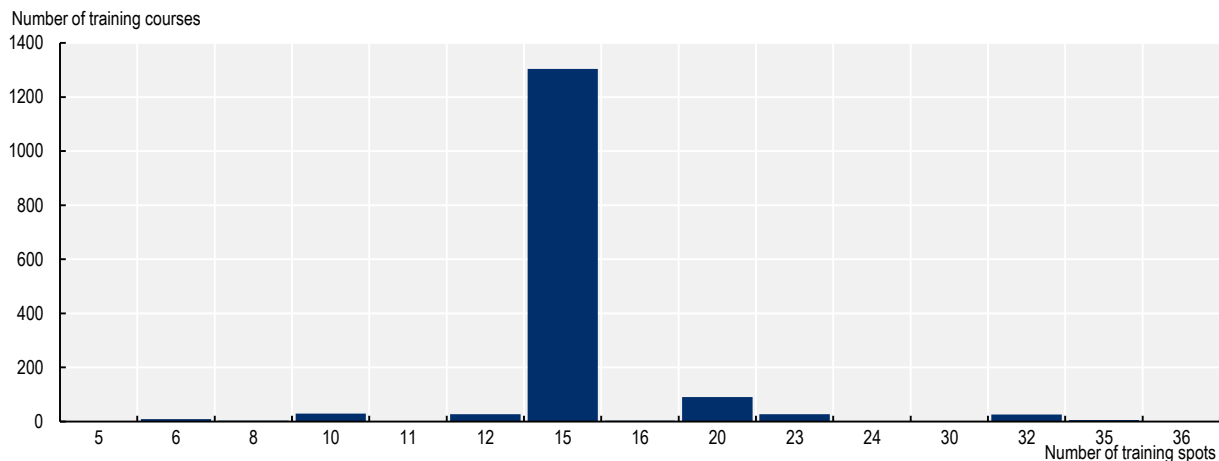


Source: OECD calculations based on data from ARPAL Umbria.

Class size

The RTC's training courses are conducted in relatively small class sizes, with most courses being open to a maximum of 15 participants. The distribution of class sizes is relatively homogenous, with courses having fewer than 10 participants or more than 32 participants being rare (see Figure 2.13).

Figure 2.13. Frequencies of the class size per training course



Source: OECD calculations based on data by ARPAL Umbria.

Research has shown mixed results regarding the impact of class size on learning outcomes. Some studies have suggested that smaller class sizes are associated with better academic performance and student engagement, while others have found no significant correlation (see also Box 2.7.). However, smaller class sizes do allow for more personalized attention from instructors and greater opportunities for student participation and interaction. Furthermore, smaller class sizes may be particularly beneficial for training courses that involve hands-on or practical learning, as it allows for greater individualized attention and support from trainers. This could be particularly important for low-skilled occupations that require more intensive training to acquire necessary skills.

Box 2.7. The class size: What is the impact on learning outcomes?

Smaller class sizes are often thought to be beneficial to students' learning outcomes (OECD, 2016^[11]). Teachers can focus more on the needs of individual students when they are teaching in smaller classes. They can distinguish between stronger and weaker students and spend more time for students that lag behind. Smaller classroom sizes are especially beneficial for disadvantaged students, who really benefit from having more individualised focus. Teachers also report that they prefer working in smaller classes (OECD, 2019^[12]).

At the same time, it remains hard to say what the optimal class size should be. The overall evidence for the benefit of smaller class sizes is weak (OECD, 2016^[11]), and most of the research is conducted for younger pupils, like primary school kids or high school kids. In the case of courses that target labour market participants, like the ones in Umbria, it is hard to say what the impact of having a small class size of 15 students is and to what extent it is beneficial to the participants of the course.

Differences between Perugia and Terni

The RTC offers courses in both of Umbria's provinces: Perugia and Terni. There are more training courses in Perugia, which makes sense as it is the larger of the two provinces both in terms of area and in terms of population. However, in terms of on which occupations the RTC focuses the most, the differences between the two provinces are not very pronounced. Occupations that are in the top 30 for Perugia are usually also in the top 30 for Terni and vice versa (see Annex 2.A). Notable exceptions are the jobs of

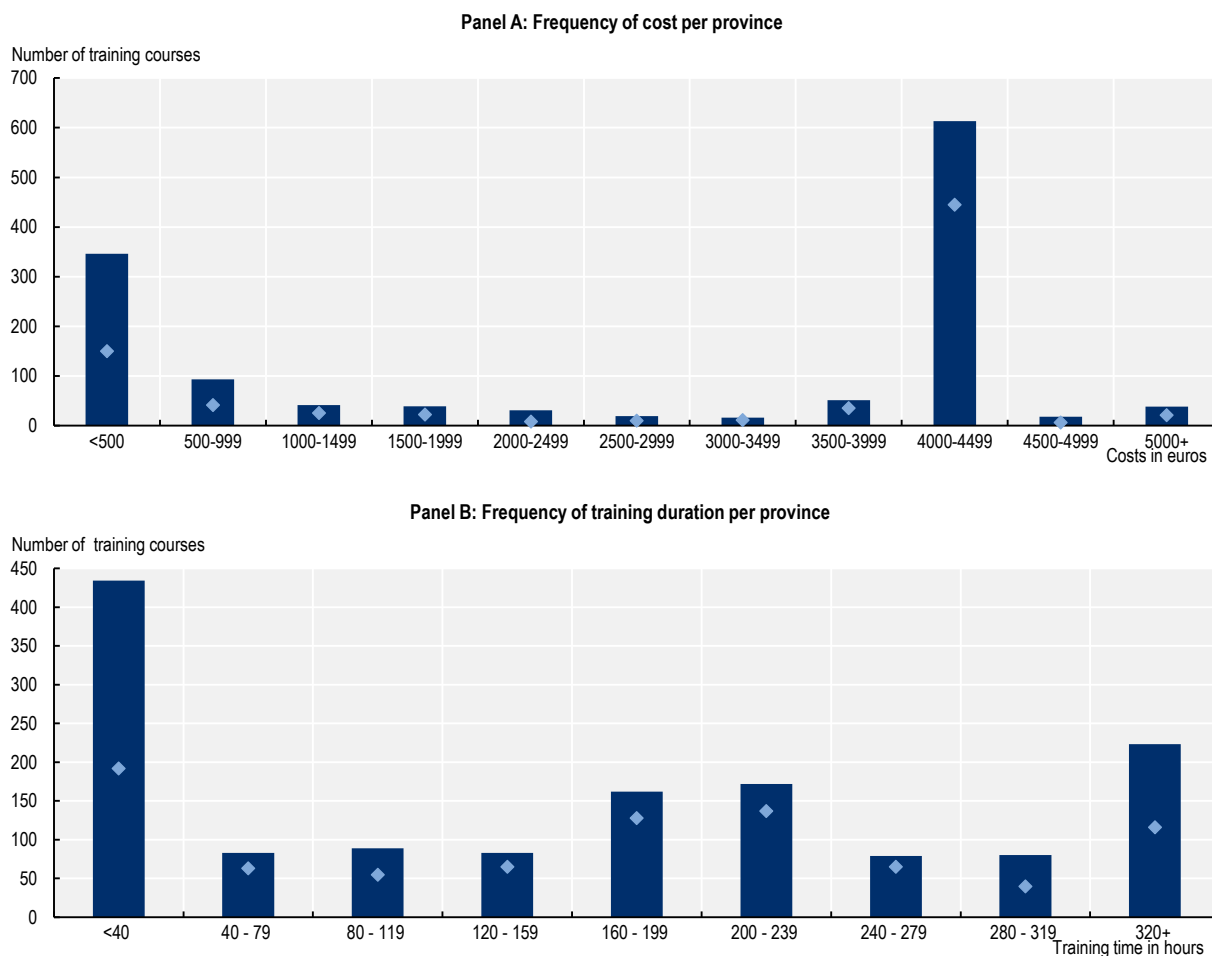
photographer, which has significantly more focus in Perugia than in Terni, and of electrical mechanic and fitter, which has more focus in Terni than in Perugia.

In terms of costs and duration however, there are noticeable differences between the two provinces. There are more relatively cheap courses in Perugia, and more relatively expensive courses in Terni (Figure 2.14, Panel A). 26.5% of courses in Perugia is below EUR 500, while the same is true for 19.4% of courses in Terni. At the same time, 46% of Perugia's courses costs EUR 4 000, compared to 57% of courses in Terni. The share of courses that cost over EUR 5 000, however, is very similar: 2.9% in PG and 2.7% in TR.

For the most part, this is likely due to the differences in course duration for the two provinces, which are presented in Figure 2.14, Panel B. There is a significantly larger percentage of short courses in Perugia, as 30.9% of courses are less than 40 hours. In Terni, only 22.3% of courses has that length. 30.8% of courses in Terni instead has a moderate length in between 160 and 239 hours, which can be said of 23.8% of courses in Perugia. From the previous analysis we know that courses of this length are more likely to be around EUR 4 000, which can explain the difference in costs that was observed. Differences in costs and duration:

At the same time, there is a larger percentage of courses of over 320 hours in Perugia than in Terni, 15.9% versus 13.5%, while the difference in the percentage of the most expensive courses was not that pronounced. That must mean that some of these longest courses in Perugia still do not pass the EUR 5 000 threshold.

Figure 2.14. Frequencies of costs and duration in the two provinces



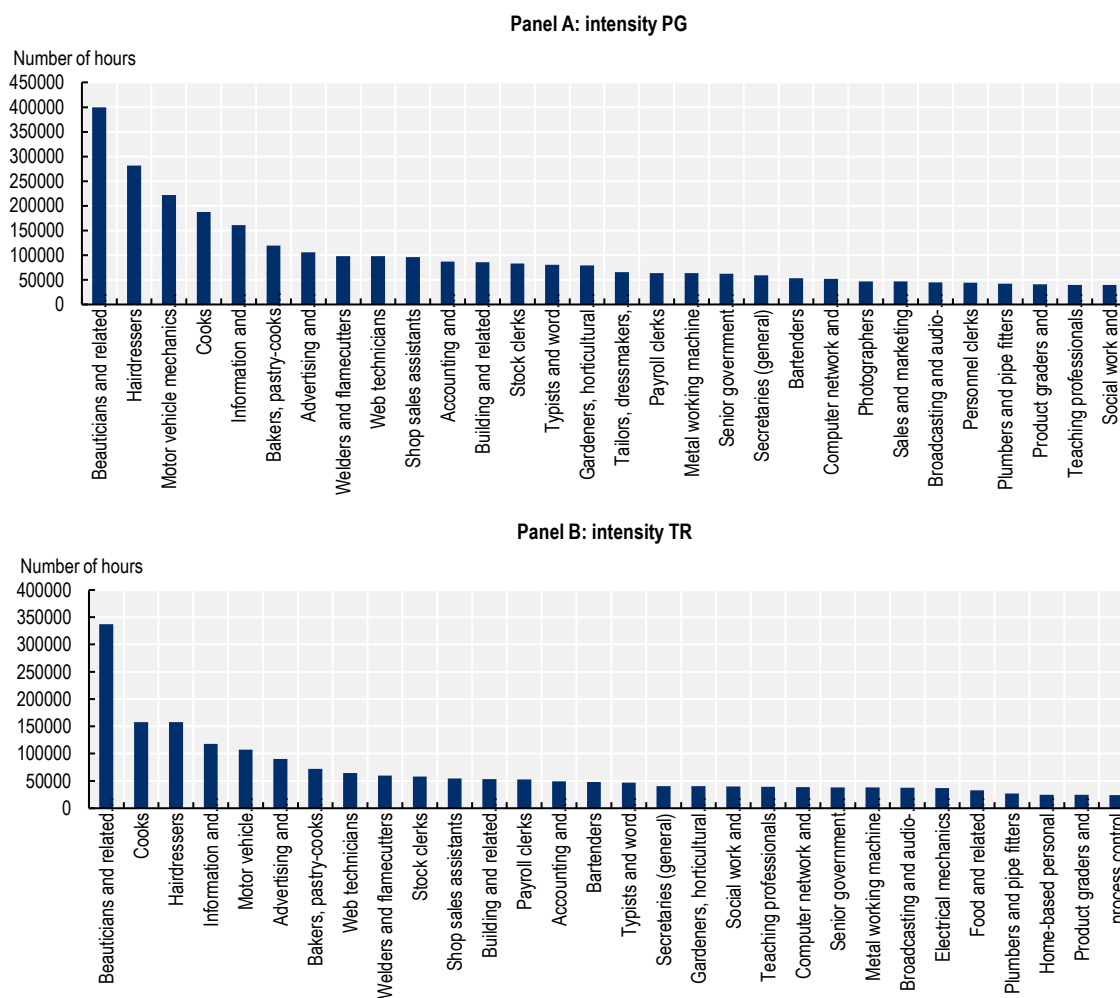
Source: OECD calculations based on data by ARPAL Umbria.

References

- ARPAL Umbria (2022), *Dataset provided to the OECD*. [5]
- ERI (2022), *Beautician Salary in Italy*, <https://www.ერი.com/salary/job/beautician/italy> (accessed on April 2023). [7]
- ERI (2022), *Computer Software Engineer Salary in Italy*, <https://www.ერი.com/salary/job/computer-software-engineer/italy> (accessed on March 2023). [10]
- ERI (2022), *Fashion Designer Salary Italy*, <https://www.ერი.com/salary/job/fashion-designer/italy> (accessed on April 2023). [9]
- Giabelli, A. et al. (2022), “WETA: Automatic taxonomy alignment via word embeddings”, *Computers in Industry*, Vol. 138, p. 103626, <https://doi.org/10.1016/j.compind.2022.103626>. [2]
- Government of Italy (1990), *Law 4 January 1990 n. 1 (legge 4 gennaio 1990, n. 1)*, https://www.mise.gov.it/images/stories/normativa/legge1_1990-attivita-estetista.pdf. [6]
- ILO (2015), *Occupational Safety and Health (OSH) - Italy*, https://www.ilo.org/dyn/legosh/en/f?p=14100:1100:0::NO::P1100_ISO_CODE3,P1100_SUBCODE_CODE,P1100_YEAR:ITA,,2015 (accessed on March 2023). [3]
- Istat (2021), *Nomenclatura e classificazione delle Unità Professionali [Nomenclature and Classification of Professional Units]*, <https://professioni.istat.it/sistemainformativoprofessionioni/cp2011/?db=2021>. [1]
- OECD (2023), “Average annual wages”, *OECD Employment and Labour Market Statistics* (database), <https://doi.org/10.1787/data-00571-en> (accessed on 13 April 2023). [8]
- OECD (2019), *TALIS 2018 Results (Volume I): Teachers and School Leaders as Lifelong Learners*, TALIS, OECD Publishing, Paris, <https://doi.org/10.1787/1d0bc92a-en>. [12]
- OECD (2017), *Getting Skills Right: Italy*, Getting Skills Right, OECD Publishing, Paris, <https://doi.org/10.1787/9789264278639-en>. [4]
- OECD (2016), *PISA 2015 Results (Volume II): Policies and Practices for Successful Schools*, PISA, OECD Publishing, Paris, <https://doi.org/10.1787/9789264267510-en>. [11]

Annex 2.A. Selection of results at the province level

Annex Figure 2.A.1. The top 30 occupations with the highest number of training hours per occupation in Perugia and Terni



Note: PG = Perugia; TR = Terni.
 Source: OECD calculations based on a dataset by ARPAL.

Annex Table 2.A.1. Top 30 occupations in Perugia, with their training hours, number of training courses and ranking in both regions

| ISCO code | ISCO name | Training hours PG | Training hours TR | Frequency PG | Frequency TR | Training hours rank PG | Training hours rank TR | Frequency rank PG | Frequency rank TR |
|-----------|--|-------------------|-------------------|--------------|--------------|------------------------|------------------------|-------------------|-------------------|
| 5142 | Beauticians and related workers | 399390 | 337260 | 55 | 39 | 1 | 1 | 1 | 1 |
| 5141 | Hairdressers | 281640 | 157800 | 32 | 28 | 2 | 3 | 4 | 5 |
| 7231 | Motor vehicle mechanics and repairers | 221750 | 107300 | 45 | 29 | 3 | 5 | 2 | 3 |
| 5120 | Cooks | 187560 | 157860 | 31 | 29 | 4 | 2 | 6 | 3 |
| 3512 | Information and communications technology user support technicians | 161130 | 118005 | 41 | 33 | 5 | 4 | 3 | 2 |
| 7512 | Bakers, pastry-cooks and confectionery makers | 119220 | 72180 | 32 | 19 | 6 | 7 | 4 | 7 |
| 2431 | Advertising and marketing professionals | 105796 | 90045 | 27 | 24 | 7 | 6 | 7 | 6 |
| 7212 | Welders and flamecutters | 98220 | 59880 | 26 | 16 | 8 | 9 | 9 | 10 |
| 3514 | Web technicians | 98175 | 64425 | 27 | 19 | 9 | 8 | 7 | 7 |
| 5223 | Shop sales assistants | 96270 | 54630 | 25 | 15 | 10 | 11 | 10 | 11 |
| 4311 | Accounting and bookkeeping clerks | 86745 | 49170 | 24 | 14 | 11 | 14 | 12 | 14 |
| 7411 | Building and related electricians | 85920 | 53610 | 25 | 15 | 12 | 12 | 10 | 11 |
| 4321 | Stock clerks | 82935 | 58290 | 24 | 17 | 13 | 10 | 12 | 9 |
| 4131 | Typists and word processing operators | 80700 | 46890 | 21 | 14 | 14 | 16 | 14 | 14 |
| 6113 | Gardeners, horticultural and nursery growers | 78855 | 40176 | 20 | 12 | 15 | 18 | 15 | 17 |
| 7531 | Tailors, dressmakers, furriers and hatters | 65535 | 24060 | 17 | 7 | 16 | 31 | 17 | 27 |
| 4313 | Payroll clerks | 63750 | 52725 | 19 | 15 | 17 | 13 | 16 | 11 |
| 7223 | Metal working machine tool setters and operators | 63495 | 37950 | 17 | 10 | 18 | 23 | 17 | 22 |
| 1112 | Senior government officials | 62340 | 38040 | 16 | 10 | 19 | 22 | 19 | 22 |
| 4120 | Secretaries (general) | 59325 | 40530 | 16 | 12 | 20 | 17 | 19 | 17 |
| 5132 | Bartenders | 53505 | 48150 | 15 | 14 | 21 | 15 | 21 | 14 |
| 3513 | Computer network and systems technicians | 51750 | 38695 | 15 | 10 | 22 | 21 | 21 | 22 |
| 3431 | Photographers | 46530 | 20760 | 13 | 6 | 23 | 36 | 23 | 35 |
| 1221 | Sales and marketing managers | 46425 | 22275 | 13 | 7 | 24 | 34 | 23 | 27 |
| 3521 | Broadcasting and audio-visual technicians | 44700 | 37740 | 13 | 11 | 25 | 24 | 23 | 20 |
| 4416 | Personnel clerks | 43800 | 23400 | 13 | 7 | 26 | 32 | 23 | 27 |
| 7126 | Plumbers and pipe fitters | 42330 | 26670 | 12 | 7 | 27 | 27 | 27 | 27 |

| ISCO code | ISCO name | Training hours PG | Training hours TR | Frequency PG | Frequency TR | Training hours rank PG | Training hours rank TR | Frequency rank PG | Frequency rank TR |
|-----------|---|-------------------|-------------------|--------------|--------------|------------------------|------------------------|-------------------|-------------------|
| 7543 | Product graders and testers (excluding foods and beverages) | 41055 | 24660 | 12 | 7 | 28 | 29 | 27 | 27 |
| 2359 | Teaching professionals not elsewhere classified | 39840 | 39210 | 11 | 11 | 29 | 20 | 29 | 20 |
| 2635 | Social work and counselling professionals | 39687 | 40080 | 11 | 12 | 30 | 19 | 29 | 17 |

Source: OECD calculations based on a dataset by ARPAL.

Notes

¹ <https://www.arpalumbria.it/catalogo-regionale-dellofferta-formativa#>

² In addition, data show that not all training programmes are classified into an ISTAT occupation. Out of all training courses in the RTC, 64% target a specific occupation. More details are provided throughout the text.

³ They range between around 313 000 hours to 186 000 hours.

⁴ Courses for high skilled occupations represent the 34.9% of the total courses offered, while those for low skilled workers are approximately 20.9% (Figure 2.3). The majority of training opportunities (44.1% of the total) instead targets medium-skill occupations.

⁵ Jointly, these four jobs receive 41.4% of all high-skill training hours, showing the attention that the RTC is paying attention to the strengthening of people's digital skills, which are increasingly important due to the impact of digitalisation.

⁶ This makes it possible to present them all instead of showing a selection. Showing just the top ten would give the impression that the RTC for example focuses quite many training hours on the position of waiter, as it is tenth on the list. However, this occupation would not make the top 10 in any of the other skill levels, although it is ranked 47th out of all 81 occupations.

⁷ It should be noted that, in ISCO, cooks and waiters are combinations of multiple ISTAT occupations. The distinction within ISTAT is made based on where the jobs are being performed. There are separate ISTAT codes for cooks in hotels and restaurants and for cooks who work in shops and fast-food restaurants for example *Cuochi in alberghi e ristoranti, Addetti alla preparazione, alla cottura e alla vendita di cibi in fast food, tavole calde, rosticcerie ed esercizi assimilate*. The same also holds for waiters, *Camerieri di ristorante, Esercenti di ristoranti, fast food, pizzerie ed esercizi assimilati*.

⁸ This makes it possible for Chapter 3 to look at the relative alignment between the skills taught in the RTC and the skills that are demanded in OJPs.

⁹ A list with the top 32 skills is reported instead of a top 30, as the last 7 skills all have the same share.

¹⁰ In this analysis, the number of potential participants for a course is equal to the number of open training spots in that course. This means that the shares in Figure 2.4 do not add up to 100%, as courses often teach more than one skill, and skills can overlap between different training courses. So, a participant in a course for cooks can for example learn how to operate in the catering sector as well as learn proper hygiene in cleaning the catering workplace, and a participant in a course for waiters could likewise learn hygiene in cleaning the catering workplace. In this example, one person learned how to operate in the catering sector, and 2 people learned how catering workplace hygiene, even though there were only 2 participants in the training courses.

¹¹ The description in Italian reads as: "Acquisire le conoscenze utili a definire gli aspetti contrattuali della prestazione professionale e a comprendere gli adempimenti necessari al corretto esercizio di un contratto di lavoro autonomo o parasubordinato".

¹² Health and safety in Italy have been discussed in more detail in Chapter 1.

¹³ The skill of managing files (gestire file) is potentially another digital skill, but it is not possible to establish that for certain.

¹⁴ The similarity between the RTC skill and the skills into which they are mapped is taken into account to create the new statistics. This is done by weighing the results in Figure 2.5 by the similarity score. For example, directly after mapping the RTC skills to the Lightcast skills, the skill “regulations_safety_firefighting” is taught to 53% of potential participants. The skill “regulations_safety_firefighting” is a match for five different skills in the RTC, including for example work_safety, and “fire_prevention_firefighting_emergency_management”, which add up to 53% of potential participants. However, because “regulations_safety_firefighting” is not an exact match for any of these five skills which are described in the language of the RTC, its prevalence is adjusted downwards to 42.5%.

¹⁵ More details can be found in Annex A. Manual investigation of the results led to the correction of a number of cases.

¹⁶ It remains, however, unclear whether the price of some of those courses was aligned to their market value or if, instead, simply aligned to the resources made available the government. Training vouchers are not active anymore and courses are not currently subsidised. The data on the RTC does not, however, allow to track whether discontinuing training vouchers has had any impact on training cost.

3

The alignment between training offered in the Regional Training Catalogue and the labour market

This chapter examines the alignment between the courses listed in the Regional Training Catalogue (RTC) and the demands reflected in online job postings, considering both sought-after occupations and skills. Utilising Natural Language Processing techniques, the chapter analyses the quantitative and qualitative match between the course content and the skill demand for each occupation included in the RTC. A novel metric, the skill-match score, is introduced by integrating data on sought-after skills from online job postings and the representation of these skills in the courses. Additionally, the chapter offers insights into potential areas where training may not yet adequately meet demand or exceed it within the analysed occupations and skill sets. These findings serve as preliminary indicators for policymakers, aiding in interventions to enhance training offerings or allocate resources accordingly.

Highlights

- Analysis in this chapter shows a significant misalignment between the focus of training options in the Regional Training Catalogue (RTC) and the occupations for which the labour market demand is relatively strong (as measured by the volume of online job postings, OJPs, collected in Umbria over the period in between 2018 and June 2022).
- The analysis combines RTC and OJPs data and reveals that approximately 290 occupations have had positive demand in the Umbria's labour market but no training options were available to learn those professions. New job postings for occupations lacking a clear training option add up to 61% of total job postings in between 2018 and June 2022 highlighting the disconnect between training needs and available learning options in the current RTC.
- The shares of OJPs for occupations for which there are no training options in the RTC are often larger for low-skill occupations. In particular, the analysis shows strong demand for certain low-skilled occupations such as freight handlers; cleaners and helpers in offices, hotels and other establishments; and manufacturing labourers not elsewhere classified. While this demand is typically unmet by specific training courses in the RTC, it is important to notice that some courses may teach overlapping skills, mitigating the extent of the real gap between demand and supply of training.
- The analysis of OJPs shows a significant demand for transversal skills such as communication, problem solving skills or basic digital skills. This demand is not currently met by the content of training options available in the RTC. Conversely, the RTC seem to focus disproportionately on providing training on health and safety in the workplace, opening to the question of whether these skills should be part of the training options in the RTC.
- Certain medium- and high-skilled occupations that are in high demand do not have available training spots in the RTC, while related professions have a surplus of training spots compared to demand in OJPs. Similarly, certain general skills that are in high demand are not taught in the RTC, while more specific but related skills are taught in many courses. These two observations point to training courses for occupations and for skills being useful to a larger number of people than originally estimated.
- New indicators and tentative evidence comparing the alignment between the quantity and quality of skills supplied in RTC with the demand of the employers in Umbria suggests that, when training is available, it aligns relatively well with skill demands in a variety of high and medium skill occupations, but that alignment is weaker across low skilled roles. Alignment at the occupation level seems to be particularly good for Advertising and Marketing professionals, Metal working machine tool settlers and operators and Building and related electricians. Instead, training for Earth moving and related plant operators, Education method specialists and Painters and related workers is relatively weaker both in terms of volume of skills demanded and taught as well as in the overall alignment of courses to the typical skill demand for those occupations as expressed in OJPs.
- The national programme for the Guarantee of Employability of Workers (GOL) is a recent initiative that aims to fill some the gaps between the need and supply of training. Preliminary evidence seems to suggest that the GOL initiative is filling some of the gaps in training options by providing new learning opportunities in occupations that are in high demand and for which the RTC training offer was relatively weak. Currently, however, the number of training courses implemented in this initiative is still limited (as one could expect due to the short-life of the initiative) and the breadth of the new training options could be extended to capture an even more varied range of skills and occupations, following also the indications contained in this report and the priorities highlighted in the results.

The previous chapter presented the courses in the RTC, along with their duration, costs, and frequencies. This chapter adds to the analysis by examining the alignment between the focus of the RTC and the demands of the labour market. Specifically, the chapter investigates whether the RTC focuses on the occupations that are in high demand in the labour market and analyses whether the courses in the RTC help people increase the skills that are in high demand in the labour market. Additionally, the chapter checks whether courses for a specific occupation teach the skills that OJPs ask for in that occupation.

Comparing the occupations in the RTC to OJPs

The comparison between the focus of the RTC and the demand in the labour market is based on information from Chapter 1 and Chapter 2. For each occupation included in the Lightcast dataset between 2018 and 2022, the chapter calculates its share in terms of the total number of OJPs.¹ Next, the chapter examines the focus of the RTC by using the total number of training spots dedicated to all occupations as a reference.² For each occupation, the chapter determines the number of training spots offered in the RTC, which is then divided by the total number of training spots. By comparing the differences between these shares, the analysis provides information regarding the alignment or misalignment between the focus of the RTC and the strength of the demand in the Umbrian labour market. It is important to note that the distance between the shares should be interpreted as an indication of areas where training falls short of (or exceeds) relative demand in the analysed occupation and that this is a preliminary signal for policy makers to intervene to boost the training offer (or divert resources to other areas), see also Box 3.1.

For example, if an occupation has a high share of OJPs but a relatively low share of training spots in the RTC, this indicates a potential misalignment issue and an area for intervention when planning future training. Conversely, if an occupation has a low share of OJPs but a high share of training spots in the RTC, it may indicate that some resources could be diverted from training in that occupation to other types of training that are associated with occupations where demand is stronger in the labour market. This analysis helps policymakers and education providers to ensure that the training offered is aligned with the needs of the labour market, which ultimately benefits individuals seeking employment and the economy as a whole.

Box 3.1. Interpreting the difference between the share of RTC's courses and the share of OJPs

The comparison between the shares of training spots offered in the RTC and the share of OJPs over the total can provide useful information regarding the alignment (or misalignment) between the focus of the RTC and the strength of the demand in the Umbrian labour market. This information can be used to highlight areas of policy intervention and the priorities for future training courses.

A few caveats apply, however, to the interpretation of some of the results in this chapter. First, the analysis does not account for cases where, despite a large volume of OJPs, this demand may be easily filled by qualified workers who could be immediately available. This is the case, for instance, where a high volume of OJPs signals frequent turnover and churn rather than pressing shortages and where the pool of qualified jobseekers is already sufficient to fill that demand.

Nonetheless, boosting resources for training in such roles will still put the clients of the PES in a position to develop labour market relevant skills and to compete with other candidates also in roles where turnover is considerable. While this does not directly solve shortages in the local labour market, it does increase the chances of unemployed to compete for new positions that are indeed opened frequently in the labour market.

It is also worth noting that enrolling in courses supplied in the RTC is not the only way through which individuals can acquire training. Data on other training providers (and provision) are, however, not accounted for in the calculations in this chapter while the focus of the analyses is solely on the relative alignment of the RTC to the local labour market demands.

Finally, areas where the gap between relative demand and supply may be small can simply reflect both a low demand and a low supply and not necessarily signal 'good quality' alignment. The text below instead focuses the attention on highlighting those occupations for which the training offer could be boosted and those for which creating new training courses is of lower priority than for occupations that are in high demand.

Firstly, there are 290 occupations for which there are no courses in the RTC, but for which the share of OJPs adds up to 61% in between 2018 and June 2022. This means that the courses in the RTC do not directly cover the occupations that are the target of the majority of OJPs. Table 3.1 shows all of the occupations for which at least 1% of OJPs have been published over the period of analysis, but do not have an accompanying training offer in the RTC. Additionally, Figure 3.1 shows all 12 of the occupations for which there are training spots in the RTC, but for which the share of OJPs exceeds the share of training spots, signalling the need to further improve resources for training.

Based on the information in Table 3.1 and Figure 3.1, the RTC is significantly lacking in focus on occupations that are in high demand. For instance, the occupations in Table 3.1 correspond to 18397 OJPs in between January 2018 and June 2022, for which there was no training. Additionally, in Figure 3.1 there are 6 occupations for which the share of OJPs is larger than 1%, but the gap between the share of OJPs and the share of training spots is also relatively large. These are the occupations: Commercial sales representatives; Software developers; Draughtspersons; Waiters; Electrical mechanics and fitters; and Shop sales assistants.

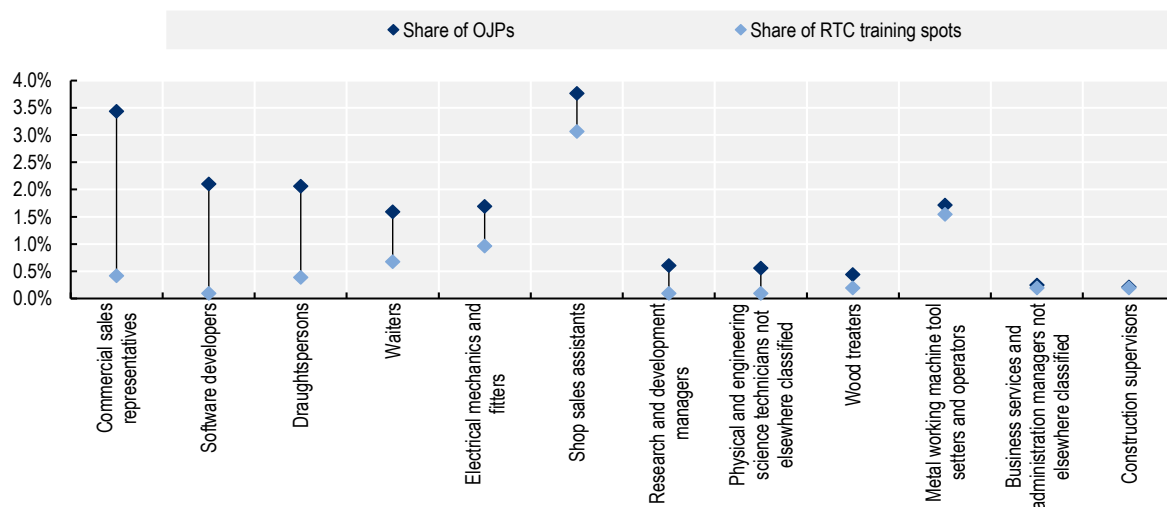
It should be noted, however, that it is possible that the RTC offers courses which are useful for multiple occupations. For instance, kitchen helpers can also benefit from following training courses that are marked for cooks. The existence of training courses that offer cross-occupational skills could help mitigate the observed discrepancies between share of OJPs and share of training spots.

Table 3.1. Occupations that are in high demand but have no training offer in the RTC

| ISCO code | ISCO name | Share of OJPs | Number of OJPs |
|-----------|--|---------------|----------------|
| 9333 | Freight handlers | 4.4% | 3187 |
| 9112 | Cleaners and helpers in offices, hotels and other establishments | 3.3% | 2390 |
| 3343 | Administrative and executive secretaries | 2.6% | 1883 |
| 9329 | Manufacturing labourers not elsewhere classified | 2.3% | 1666 |
| 8219 | Assemblers not elsewhere classified | 1.9% | 1376 |
| 2149 | Engineering professionals not elsewhere classified | 1.7% | 1231 |
| 3339 | Business services agents not elsewhere classified | 1.4% | 1014 |
| 2511 | Systems analysts | 1.2% | 869 |
| 3331 | Clearing and forwarding agents | 1.2% | 869 |
| 3323 | Buyers | 1.1% | 797 |
| 8332 | Heavy truck and lorry drivers | 1.1% | 797 |
| 2144 | Mechanical engineers | 1.1% | 797 |
| 9412 | Kitchen helpers | 1.1% | 797 |
| 4419 | Clerical support workers not elsewhere classified | 1.0% | 724 |

Note: ISCO = International Standard Classification of Occupations.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Figure 3.1. All occupations for which the demand in OJPs exceeds the training offer

Note: only occupations that have at least one RTC course targeting them are included in the graph, and only those for which the share of OJPs is larger than the share of RTC training spots are presented in the graph.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Combining the analysis from Figure 3.1 and Table 3.1 gives information on which areas could benefit from more focus by the RTC. There are quite many manual labour jobs that are in high demand, but for which the training offer is either non-existent or relatively low. For example, there is no training for positions as

freight handlers, cleaners and helpers in offices, hotels and other establishments, manufacturing labourers, assemblers, and metal working machine tool setters and operators, and the shares of training spots for waiters and for electrical mechanics and fitters are lower than the shares of OJPs. Freight handlers in particular are in high demand. More information on courses for the logistics sector can be found in Box 3.2.

It should be noted however, that it is possible that not all manual labour jobs that show a significant gap between the share the labour demand and the share of training courses in the RTC are jobs that would benefit greatly from training. For certain jobs it is not necessary to obtain certificates or diplomas before being hired. For example, perhaps it would not be efficient to offer training to become a cleaner or helper in offices, hotels and other establishments, or to become an assembler even though labour demand is rather high, if following a training does not increase someone's chances to be hired for that position.

Box 3.2. Courses in the logistics sector

While there are courses that are specific to jobs in the logistics sector, there are no courses that directly target freight handlers. Freight handlers are one of the most highly demanded professions in Umbria in between January 2018 and June 2022, as 4.4% of the total number of OJPs targets them. This is a low-skill occupation that falls within ISCO-code 9333. In Italian they are called “Addetti allo spostamento e alla spedizione dei materiali o delle merci”.

The RTC does offer courses for another prominent logistics job: stock clerks. In fact, 2.5% of the RTC's training spots are available to this occupation, compared to 1.14% of all OJPs. Stock clerks are a medium-skill profession within ISCO-code 4321, and the Italian name of this profession is “Responsabile di inventario”. The courses within the RTC target the professions: “Addetti alla gestione dei magazzini e professioni assimilate”, and “Responsabili di magazzino e della distribuzione interna”.

While it is possible that certain parts of the courses for stock clerks are relevant for freight handlers, additional specific courses for freight handles might be needed to meet the demand in OJPs. This mainly due to the differences between the tasks carried out by freight handlers and by stock clerks. These differences have briefly been discussed in Chapter 1, but crucially, freight handlers carry out physical tasks such as packing, carrying and loading items (ISCO-08), while stock clerks are in charge of keeping records and arranging and controlling the receipt of goods.

Source: OECD calculations based on data by Lightcast and data by ARPAL Umbria.

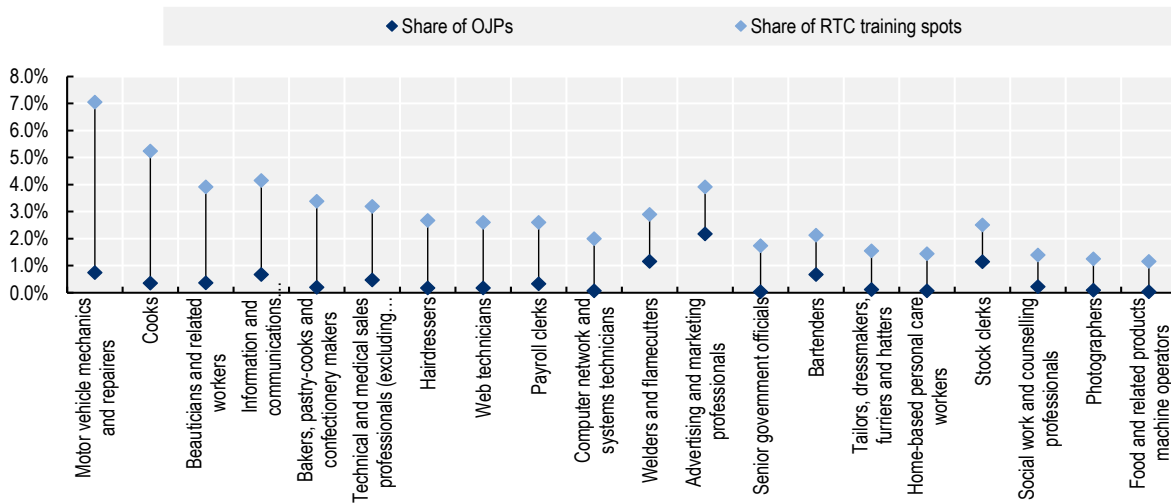
Table 3.1 and Figure 3.1 show a diverse group of occupations, that ranges over all different skill-levels, although high-skilled level jobs are slightly more represented among those in high demand and receiving less attention in the RTC. The first three occupations in Figure 3.1 are high-skilled occupations, as well as 7 out of 17 occupations in Table 3.1.³ For instance, there is a significant difference between the number of commercial sales representatives in the total number of OJPs and the relative number of available training spots for them in the RTC. Data show that commercial sales representatives represent 3.4% of the total number of OJPs, which amounts to 2463 new vacancies published in Umbria over the period of analysis. However, the RTC made available only 62 training spots, approximately 0.4% of the total number of training spots. After the discrepancy for freight handlers, the gap between the relative demand and training offer for commercial sales representatives is the largest among all occupations. Training for commercial sales representative could therefore be expanded, as demand is relatively strong.

Figure 3.2 presents a different perspective, showing the occupations that are receiving relatively intense focus in the RTC compared to their labour market demand, as observed in OJPs. In contrast to Figure 3.1, the gaps between the shares in Figure 3.2 are much larger. For instance, motor vehicle mechanics and repairers represent only 0.7% of OJPs, but 7% of the RTC's training spots are open to this occupation.⁴

Even for the occupation that ranks 20th in Figure 3.2, food and related products machine operators, the discrepancy is nearly three times larger than the average gap size. This means that the RTC has 189 spots available to train as a food and related products machine operators, while there were 32 OJPs in between January 2018 and June 2022.

Notably, Figure 3.2 shows only two occupations, advertising and marketing professionals and welders and flamecutters, which have a share of OJPs greater than 1%. The remaining 18 jobs listed in Figure 3.2 have a relatively small impact on the number of job openings, with a share of less than 1%. This seems to signal that the RTC is disproportionately focused on jobs that have relatively low demand in OJPs.

Figure 3.2. Top 20 training courses for occupations which are least demanded and most offered



Note: Only occupations that have at least one OJP targeting them are included in the graph.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Whereas the occupations that were in highest demand, with the lowest shares of training spots were often high-skilled occupations, the occupations in Figure 3.2 are mostly in the medium-skills category. There are only a few high-skilled occupations, such as architects and engineers, that receive relatively more attention in the RTC than their demand in the labour market. These findings suggest that the RTC may be focusing too much on certain medium-skill occupations, such as motor vehicle mechanics and cooks, and neglecting other occupations that are in higher demand in the labour market.

It is worth noting that occupations in specific areas (for instance the digital occupations) may be present in both sides of the spectrum, that is the RTC could either be too focused on some of these occupations, relative to their demand in OJPs, but for other the training options may not be sufficient. For instance, while the data suggest a deficit of training opportunities for software developers and systems analysts, the analysis also suggests a relative overemphasis on training offer for ICT user support technicians, web technicians, and computer network and systems technicians. These are all ICT-related jobs, which seems to signal that it can be challenging to determine which digital skills/ digital occupations to prioritise in the training offer. In this context, it is key for the PES to carry out detailed analysis of the skills that are in demand for these occupations and to work closely with industry stakeholders to ensure that training programs are tailored to the evolving needs of the labour market.

There are some limitations to the indicators produced above, however, as certain jobs that seem to receive a disproportionate focus in the RTC, are in fact less likely to be advertised online. For instance, jobs that require working in close proximity to clients such as beauticians, hairdressers, and related workers may not be advertised online as frequently. This was discussed in Chapter 1. Other jobs that are less likely to be advertised online are those related to the food industry, such as cooks; and bakers and pastry chefs. These jobs constitute a significant portion of all training spots at the RTC, with 5.2%, and 3.4% respectively, while the shares of OJPs are 0.4% and 0.2%. The demand for cooks, bakers and pastry chefs is likely to be higher in practice.

Comparing the labour demand and training opportunities across occupations of different skill levels

The shares of OJPs for occupations for which there are no training courses are often larger for low-skill occupations (Table 3.2). In particular, the previously mentioned occupations freight handlers; cleaners and helpers in offices, hotels and other establishments; and manufacturing labourers not elsewhere classified, jointly account for 10% of all OJPs. This means that while 7243 OJPs in between January 2018 and June 2022 were looking for someone to fulfil these roles, there are no training courses available in the RTC dedicated to them.

In the case of 11 out of 71 occupations with training in the RTC, the share of OJPs exceeds the share of training spots in the OJPs (Figure 3.3). Six of these occupations, are high-skill occupations like commercial sales representatives, software developers and draughtspersons. Figure 3.3 presents all of the occupations for which there is both demand in terms of OJPs, and at least one course in the RTC. For 80% of the occupations, instead, the relative share of training courses over the total exceeds the relative demand, suggesting that the RTC puts an intense focus on occupations for which the demand is relatively weak.

Table 3.2. Top 10 occupations without training spots in the RTC, per skill-level

| ISCO code | ISCO name | Skill-Level | Share of OJPs | Number of OJPs |
|-----------|--|-------------|---------------|----------------|
| 3343 | Administrative and executive secretaries | H | 2.6% | 1883 |
| 2149 | Engineering professionals not elsewhere classified | H | 1.7% | 1231 |
| 3339 | Business services agents not elsewhere classified | H | 1.4% | 1014 |
| 2511 | Systems analysts | H | 1.2% | 869 |
| 3331 | Clearing and forwarding agents | H | 1.2% | 869 |
| 3323 | Buyers | H | 1.1% | 797 |
| 2144 | Mechanical engineers | H | 1.1% | 797 |
| 2421 | Management and organization analysts | H | 0.9% | 652 |
| 2262 | Pharmacists | H | 0.8% | 579 |
| 3423 | Fitness and recreation instructors and program leaders | H | 0.7% | 507 |
| | | | | |
| 8219 | Assemblers not elsewhere classified | M | 1.9% | 1376 |
| 8332 | Heavy truck and lorry drivers | M | 1.1% | 797 |
| 4419 | Clerical support workers not elsewhere classified | M | 1.0% | 724 |
| 4312 | Statistical, finance and insurance clerks | M | 1.0% | 724 |
| 4221 | Travel consultants and clerks | M | 1.0% | 724 |
| 7421 | Electronics mechanics and servicers | M | 1.0% | 724 |
| 4226 | Receptionists (general) | M | 0.9% | 652 |
| 4110 | General office clerks | M | 0.8% | 579 |
| 7533 | Sewing, embroidery and related workers | M | 0.6% | 435 |
| 8189 | Stationary plant and machine operators not elsewhere classified | M | 0.5% | 362 |
| | | | | |
| 9333 | Freight handlers | L | 4.4% | 3187 |
| 9112 | Cleaners and helpers in offices, hotels and other establishments | L | 3.3% | 2390 |
| 9329 | Manufacturing labourers not elsewhere classified | L | 2.3% | 1666 |
| 9412 | Kitchen helpers | L | 1.1% | 797 |
| 5244 | Contact centre salespersons | L | 0.8% | 579 |
| 5242 | Sales demonstrators | L | 0.7% | 507 |
| 5249 | Sales workers not elsewhere classified | L | 0.7% | 507 |
| 5419 | Protective services workers not elsewhere classified | L | 0.4% | 290 |
| 9313 | Building construction labourers | L | 0.4% | 290 |
| 5112 | Transport conductors | L | 0.3% | 217 |

Source: OECD calculations based on Lightcast data.

The analysis shows that the RTC could benefit from offering more courses for engineering professionals. Currently, in fact, no courses are available for engineering professionals not elsewhere classified, despite a significant demand (1.7% of total OJPs). The RTC also does not provide training for mechanical engineers, industrial and production engineers, and mechanical engineering technicians. Demand for these jobs is a relatively smaller but still significant (the shares of OJPs over the total for these occupations are 1.2%, 0.6% and 0.6% respectively). Physical and engineering science technicians not elsewhere classified is one of the occupations that does have designated training in the RTC, but demand for these professionals exceeds the relative share of training spots. Instituting more engineering courses could therefore be beneficial, especially if these were to cover skills useful for multiple kinds of engineering professions.

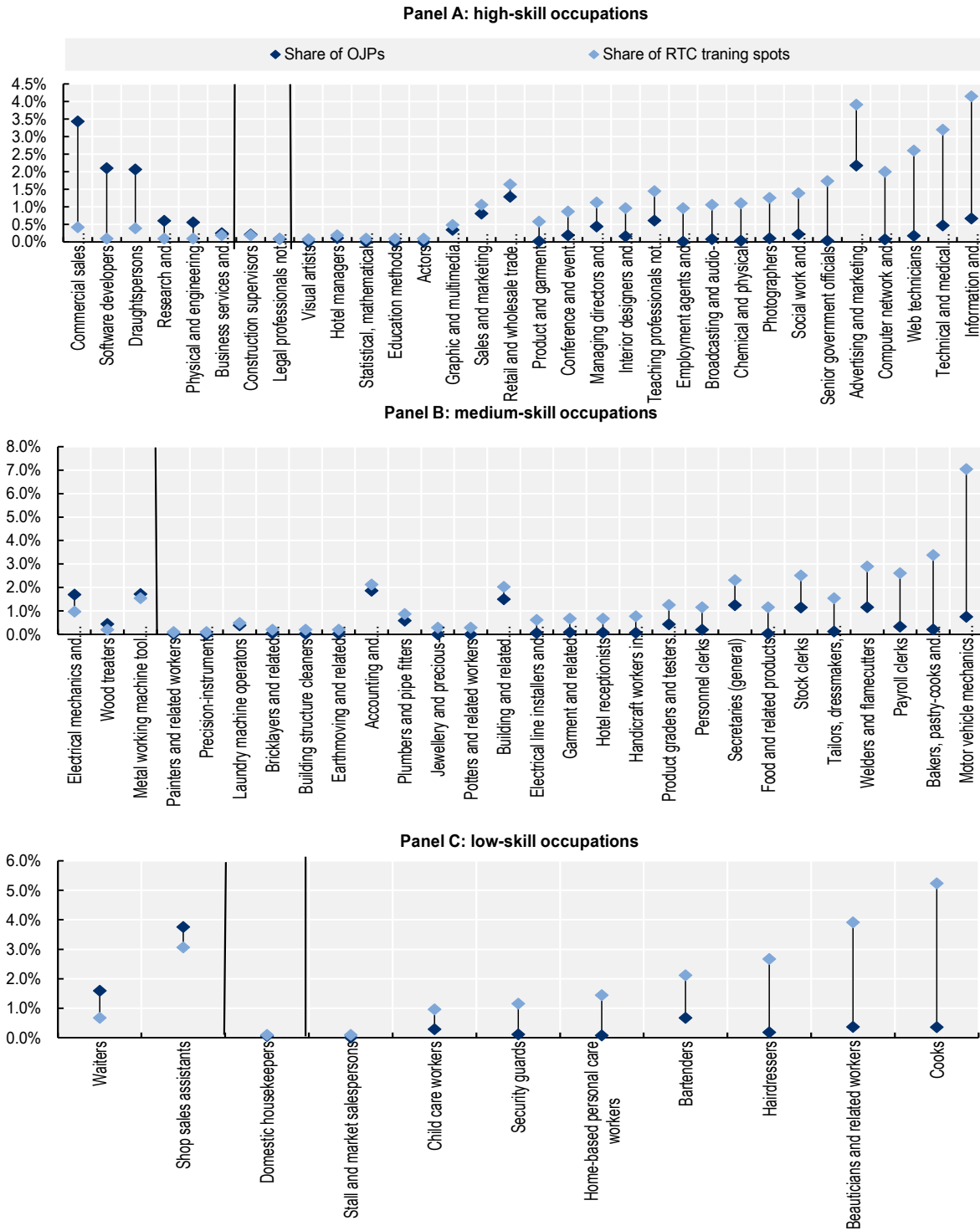
The case of managers is an interesting example of the heterogeneity in the disconnect between demand and supply of training, as the demand for certain types of managers exceeds the number of training spots, while for other types of managers there are more training spots than the share of OJPs (Figure 3.3, Panel A). For instance, the shares of OJPs for research and development managers and for business services and administration managers exceed the shares of training spots, but at the same time the share of training spots for sales and marketing managers, retail and wholesale trade managers and managing directors and chief executives is larger than the share of OJPs. Potentially, courses which are assigned to just one type of manager in the catalogue could be useful for multiple different types of managers. This would mean that there would be an overlap in the skills that are taught in the RTC, which could mitigate some of the perceived misalignment in the training offer and labour demand for managers.

For medium-skilled occupations, it stands out that there are no RTC courses for many different types of clerical jobs, which jointly make up 5.1% of OJPs (Table 3.2).⁵ However, according to Figure 3.3 Panel B there is a relatively too intense focus on certain other clerical roles like personnel clerks, secretaries (general), stock clerks and payroll clerks. Furthermore, there is even a course for typists and word processing operators, which receives 2.9% of the training spots in the RTC but has no OJPs. This indicates that there is quite a need for clerical personnel, and that while there are quite a few courses targeting these roles, the focus is not always allocated to the different types of clerical roles in a way that matches OJPs. At the same time, just like for managers, it could be the case that skills that are taught in courses for certain clerks are able to be carried over to other clerical roles. This would mean that the contents of the courses do not necessarily need to change much to align with the demand in terms of OJPs. Another subsection focuses on the skills that are taught in the courses of the RTC.

In the case of the low skill occupations that have specialised training in the RTC, the focus of the RTC seems to be too intense for most of them, compared to the demand in OJPs (Figure 3.3 Panel C). The focus seems especially disproportionate for courses for cooks, and for personal care jobs like beauticians and related workers and hairdressers. At the same time, there are no courses that are specifically allocated to kitchen helpers, although that occupation captures 1.1% of all OJPs. It could be that certain courses which are aimed at cooks or at other kinds of food service jobs are already teaching skills that are beneficial for kitchen helpers as well, or could be used as a basis to also develop courses that specifically target kitchen helpers.

Additionally, the lefthand side of Figure 3.3 Panel C shows that there is relatively little training for waiters and shop sales assistants compared to the share of OJPs for these jobs. The differences are 0.9 and 0.7 percentage points respectively. Interestingly, the share of training spots for shop sales assistants is already quite high, as 3.1% of RTC training spots are allocated to them. Scaling up the number of training spots for shop sales assistants to aligning the focus of the RTC with the share of OJPs could therefore be relatively easy. Either more participants could be allowed into the training courses, or more courses with the existing curriculum could be offered.

Figure 3.3. Alignment between share of OJPs and share of RTC training spots



Note: Only occupations that have at least one RTC course and one OJP targeting them are included in the graph. Occupations on the left of the black line(s) are occupations for which demand exceeds training offer. Occupations enclosed between two black lines have an equal share of OJPs and of training spots, while occupations on the right side of the black line(s) have more focus in the RTC than in the OJPs.
 Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Comparing the alignment between the demand for skills and the skills taught in the RTC

This subsection analyses the skills on which the RTC focuses the most and the least, and compares their offer to the relative demand for those skills in the description used by employers to advertise vacancies (OJPS).

In total, the RTC makes available a large number of potential training options that sum up to around 24000 individual training spots across all training types. This section presents indicators of the share of prospective learners that could acquire a specific skill (if enrolling in one of the available courses), relative to the total number of potential participants. As this analysis focuses on the alignment between skills demanded in OJPs and skills that learners could acquire through RTC courses, all training courses are included, not just the training courses that target a specific occupation.

The share of people learning a certain skill is compared with the share of OJPs that require that specific skill. The difference between these shares can be used as a first indication of whether the RTC is focusing on skills that are highly demanded in the labour market, or whether training priorities could be updated and the training offer in RTC modified to better align to skill demands observed in OJPs.

When interpreting the results, it is worth noting that there are some limitations in the ability of these indicators to fully capture the alignment between the skill demanded and those offered. One aspect relates to the fact that some skills may not be explicitly mentioned in OJPs. Being able to write emails may be implicit in some OJPs for secretaries, but knowledge of office software be still a key aspect of the job. If so, results looking at the gap between the skills offered in the courses and those demanded by employers may be biased upward (pointing to excess of supply), in particular if certain skills are indeed offered in RTC training but not explicitly mentioned in OJPs. Similarly, some skills provided in the RTC may be synonyms of keywords used in OJPs but still hard to match to the jargon used by employers. In this case, results may be biased downwards, incorrectly signalling that skill offer is inferior relative to the demand.

While there are many different skills in both the RTC and in the OJPS in Umbria, there is a limited number of skills that are present in both. There are 2 325 skills in the RTC, after matching them to the skills in the language of all OJPs, and there 1 888 skills in the OJPs in Umbria in between January 2018 and June 2022. However, there is not a lot of overlap between these skills, only 6% is both taught and demanded on the Umbrian labour market. This signals that the content of the RTC courses can be largely adjusted to better align the skill demands stemming from the labour market.

Table 3.3 shows the 20 skills with the highest demand, which are not part of the curriculum of the RTC, and Figure 3.4 shows the skills that are taught in the RTC, but are in high demand relative to the supply in training options. The average discrepancy between training supply and demand on the labour market is 0.8 percentage points, which means that even the discrepancy for the last entry in Table 3.3 is 4.3 times larger than average.

Table 3.3. Top 20 Skills that are in high demand but have no explicit training modules in the RTC

| Italian name of the skill | Translation of the skill | Share of OJPs | Number of OJPs |
|-------------------------------|----------------------------|---------------|----------------|
| servizio clienti | customer service | 14.8% | 10720 |
| principi bilancio | budget principles | 12.4% | 8982 |
| creare soluzioni problemi | create problem solutions | 10.7% | 7750 |
| comportarsi modo responsabile | behave responsibly | 8.7% | 6302 |
| standard qualità | quality standards | 7.6% | 5505 |
| software ufficio | office software | 7.6% | 5505 |
| utilizzare sistemi ufficio | use office systems | 6.7% | 4853 |
| guidare altri | guide others | 5.9% | 4274 |
| pensare modo proattivo | think proactively | 5.9% | 4274 |
| creazione spirito gruppo | group spirit creation | 5.9% | 4274 |
| database | database | 5.6% | 4056 |
| pensare modo analitico | think in an analytical way | 5.2% | 3767 |
| gestire tempo | manage time | 5.0% | 3622 |
| guidare gruppo | lead group | 5.0% | 3622 |
| budgetary principles | budgetary principles | 4.9% | 3549 |
| osservare norme aziendali | observe corporate rules | 4.2% | 3042 |
| communication | communication | 3.9% | 2825 |
| lavorare indipendentemente | work independently | 3.9% | 2825 |
| economia | economy | 3.4% | 2463 |
| precision | precision | 3.4% | 2463 |

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

As is to be expected, (almost) all of the most highly demanded skills are transversal skills, especially the skills for which there currently is no explicit training offer. The first reason being that transversal skills pertain to many different occupations and can therefore be demanded in OJPs across sectors, which increases the share of OJPs that ask for these skills. Secondly, skills that are very general like “adapting to change”, which is demanded by around 30% of OJPs, can be difficult to train for. This makes it harder to integrate them into the RTC curriculum, which leads to a low share of training spots. Lastly, it is possible that training courses in the RTC teach their students specific ways to incorporate the more generally demanded skills. For example, instead of explicitly teaching students how to work in a team (demanded by 24% of OJPs), they could be teaching students how to guide others, or how to motivate team members. In that case, the misalignment in terms of skills is smaller than it seems at first glance. It could be beneficial to see how teamwork or knowledge about group dynamics are already incorporated in different courses, and how this could be improved to meet the needs on the labour market.

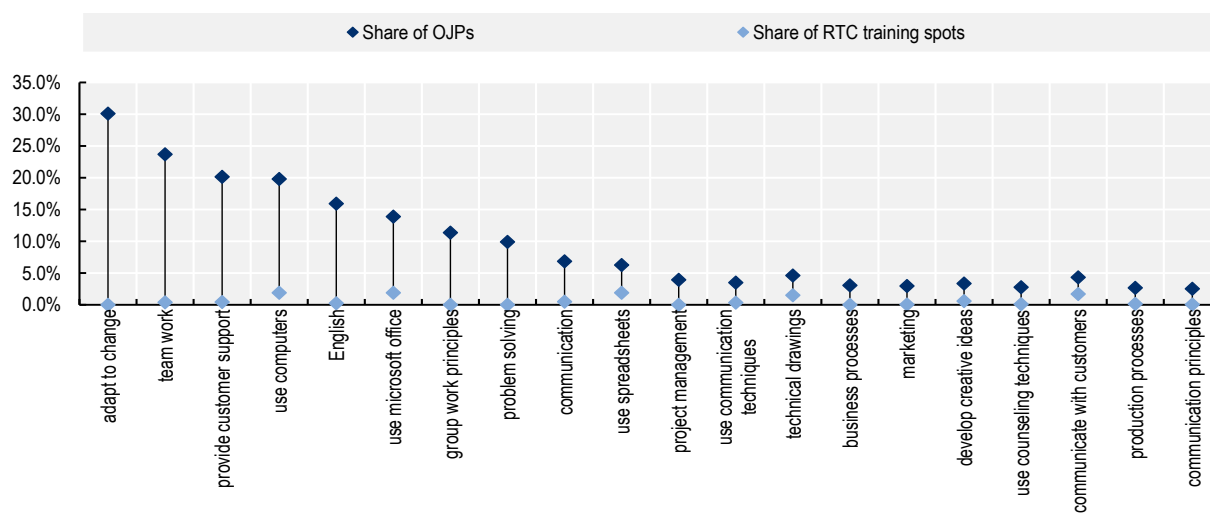
There are several digital skills that are in high demand on the labour market, with limited to no training allocated to them. For instance, knowing how to use a computer, and being able to use Microsoft office. There are some training courses that teach people how to use a computer and Microsoft office skills, as 1.9% of training spots teach these skills (Figure 3.4). The shares for demand in the labour market are 19.8% and 13.9% respectively. In Table 3.3, office software and how to use office systems are mentioned as highly demanded skills as well, at 7.6% and 6.7% of OJPs. While white-collar jobs are often overrepresented among the OJPs, these basic digital literacy skills are important skills generally. Potentially, the RTC is not providing these courses because it is assumed that the target audience is

already aware of how to perform these tasks, or it could be that the need for these courses has not been signalled yet.

Knowledge of the English language is in high demand across OJPs (15.9% of OJPs ask for proficiency in this language). The cluster analysis in Figure 2.6 in Chapter 2 already showed that the current catalogue does not have a particularly strong focus on English. In fact, only 0.2% of all participants in the RTC are in a course that specifically mentions English as a skill in their course guide. Including working knowledge of English into more RTC courses could therefore be a strategic move, given that 18760 OJP in between January 2018 and June 2022 demanded explicitly knowledge of this language.

Providing assistance to clients and customer service are two skills that are also in high demand (10.1% and 14.8% of the OJPs respectively). Again, courses are either not present or less than 1% of potential participants is learning about these skills. This is rather unexpected as the RTC had a strong focus on the cluster that included skills and knowledge of customer management and the cluster with the management of services and processes and the evaluation of quality (see Chapter 2). This could be an indication that what is mentioned in the course guides of the RTC is in close to what is demanded in the OJPs, but does not exactly match.

Figure 3.4. Top 20 skills which are most demanded and least offered



Note: Only the skills that are both present in the RTC and in the OJPs are included in the graph.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Unlike for the occupations, most of the skills that the RTC focuses on intensely, are not at all demanded on the labour market. For that reason, both skills that are demanded in OJPs and those that do not capture any of the demand in OJPs are presented in Table 3.4. Only two skills that are demanded in the OJPs make the top 30 in Table 3.4.⁶

Health and safety related skills are the skills in the RTC which receive the most disproportionate attention compared to share of OJPs that shows demand for them.⁷ Demand for health and safety skills is non-existent in OJPs, but at the same time the cluster for work safety is the largest cluster of skills that is being taught in the RTC, as was already discussed in Chapter 2. While work safety training courses might not directly improve someone's chances to get hired on the labour market, they do provide a service which is mandatory in Italy, although these training courses could also be provided elsewhere.

The skills that are present in Table 3.4 are often of a much more specific nature than the skills that are in high demand on the labour market. For instance, using software to manage client relations (18% of training

spots), and promoting communication in the internal organisation (16% of training spots). These skills can be seen as a more specific subset of general skills such as customer relations and communication.

Table 3.4. Top 30 skills which are least demanded and most offered

| Italian name of the skill | Translation of the skill | Share of RTC training spots | Number of training spots |
|---|--|-----------------------------|--------------------------|
| sicurezza lavoro | work safety | 53% | 12530 |
| gestire attività modo indipendente | manage business independently | 49% | 11501 |
| valutare qualità servizi | evaluate service quality | 34% | 8047 |
| analizzare processi influenzano erogazione assistenza sanitaria | analyze processes affecting health care delivery | 24% | 5777 |
| gestire conoscenze commerciali | manage commercial knowledge | 20% | 4689 |
| misure igiene luogo lavoro | workplace hygiene measures | 19% | 4479 |
| utilizzare software gestione relazioni clienti | use customer relationship management software | 18% | 4265 |
| gestione relazioni clienti | customer relationship management | 20% | 4782 |
| promuovere comunicazione interno organizzazione | promote internal organization communication | 16% | 3731 |
| garantire parità genere luogo lavoro | ensure gender equality in the workplace | 11% | 2717 |
| fornire assistenza pianificazione programmazione produzione | provide production planning assistance | 10% | 2428 |
| mantenere sistemi comunicazione interni | maintain internal communication systems | 9% | 2228 |
| gestire qualità pellami durante intero processo produttivo | manage leather quality during the entire production process | 9% | 2140 |
| organizzare partecipazione manifestazioni internazionali | organize participation in international events | 9% | 2106 |
| valutare esigenze produzione pianificare programma produzione | assess production needs plan production schedule | 8% | 1992 |
| analizzare processi produttivi migliorarli | analyze production processes and improve them | 8% | 1990 |
| applicare standard qualità interazione candidati | apply candidate interaction quality standards | 7% | 1772 |
| stabilire relazioni commerciali | establish business relationships | 7% | 1708 |
| lavorare équipe settore alberghiero | working as a team in the hotel sector | 7% | 1554 |
| gestire sistemi software gestione richieste pianificazione | manage planning request management software systems | 7% | 1541 |
| gestire piazzale stazione servizio | manage the service station square | 6% | 1480 |
| gestire risorse esterne | manage external resources | 6% | 1407 |
| pianificare attività produzione | plan production activities | 6% | 1407 |
| utilizzare software pianificazione produzione | use production planning software | 6% | 1385 |
| coordinare attività | coordinate activities | 6% | 1375 |
| fornire assistenza produzione documentazione laboratorio | provide assistance in the production of laboratory documentation | 6% | 1343 |
| gestione impianti organizzazione | plant management organization | 6% | 1309 |
| legislazione ambientale | environmental legislation | 6% | 1306 |
| controllare condizioni ambientali lavorazione | check processing environmental conditions | 5% | 1240 |
| coordinare comunicazione interno gruppo | coordinate internal group communication | 5% | 1214 |

Note: work safety is the maximum of: regulations_safety_firefighting, legislation_matter_health_safety_higiene, respect_regulations_safety_work, health_safety_place_work, legislation_matter_safety_mine.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Comparing the alignment between the demand for skills and the skills taught in the RTC in courses for different skill-levels

In general, there seems to be substantial misalignment when it comes to the demand for skills in the OJPs and the share of training spots in courses that teach these skills, at all different skill-levels. For instance, only 2.2% all of the skills that are either demanded for low-skilled occupations or taught in the RTC, have an overlap between demand and training offer. The same holds for 3.1% of skills for medium-skilled occupations, and 2.6% of skills for high-skilled occupations.

There are several skills that are highly demanded in OJPs for multiple different skill-levels, which the RTC does not teach. Table 3.5 shows these thirteen skills, which are all part of the top 20 of at least two out of the three skill-levels. When a cell in Table 3.5 is empty, that either means that the demand for this skill lower, which means that the skill did not reach the top 20, or that there is at least one course at that skill-level that teaches it.

Some of the skills which have an empty cell in Table 3.5 can be found in Figure 3.5. Figure 3.5 shows the skills per skill-level for which the demand in terms of OJPs is greater than the number of training spots in the RTC. For instance, demand for people that speak English is 22.8% for high-skill OJPs, and 11.6% for medium-skill OJPs, without any courses (Table 3.5). It is actually highly demanded within low-skilled OJPs as well, it is mentioned in 8.9% of OJPs, but there are low-skilled courses that teach this skill: 1.6% of low-skill training spots are in courses which feature English (Figure 3.5 Panel C). So, even though there is more demand for medium- and high-skilled workers to have a working knowledge of English, the only courses that focus on it are being taught to low-skilled workers. Potentially, it is assumed that the other skill-levels already possess English-language skills, or the need for English training for these skill-levels was not visible.

While there are only a few skills that are part of the RTC curricula for which demand exceeds the share of training spots, there are a significantly higher number of skills that are in high demand, which are not part of any of the RTC's courses. This is why there are only 25 skills presented in Figure 3.5, while there are a total of 236 skills for high-skill occupations, 104 skills for medium-skill occupations and 66 skills for low-skill occupations for which there is demand in at least 1% of OJPs, without being part of any of the courses.⁸ This shows that it is difficult to pinpoint the skill needs of the labour market, as most of the highly demanded skills are not being taught at all.

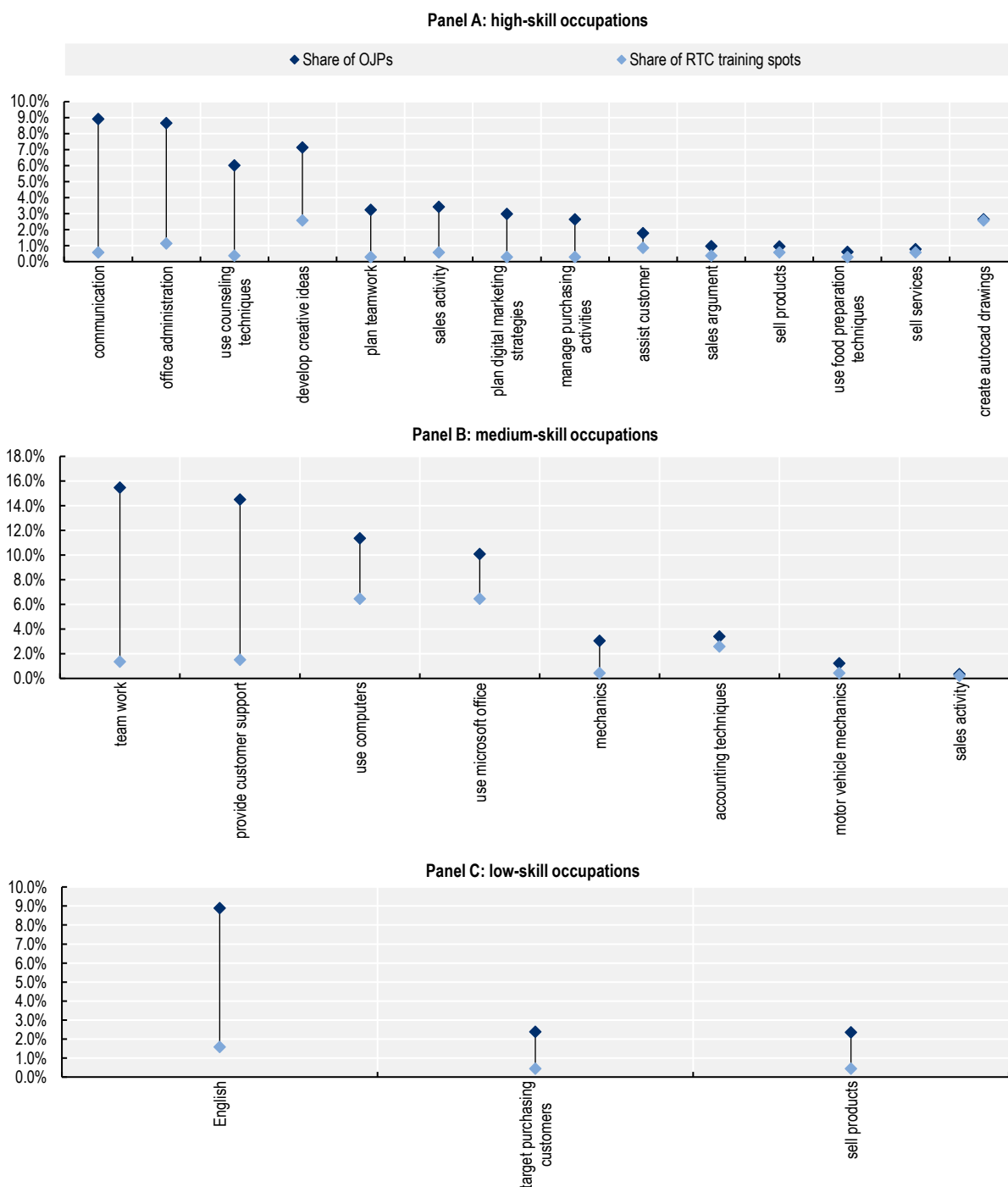
Table 3.5. Skills that are in high demand that are not offered in the RTC, which are among the top 20 highly demanded skills for multiple skill levels

| Italian name of the skill | Translation of the skill | Share of High-skill OJPs | Share of Medium-skill OJPs | Share of Low-skill OJPs |
|-------------------------------|--------------------------|--------------------------|----------------------------|-------------------------|
| budgetary principles | budgetary principles | | 6.00% | 5.6% |
| comunicazione | communication | | 4.80% | 5.6% |
| creare soluzioni problemi | create problem solutions | 15.70% | 7.3% | 5.6% |
| inglese | English | 22.80% | 11.6% | |
| guidare altri | guide others | 11.10% | | 2.9% |
| principi bilancio | budget principles | | 16.00% | 14.3% |
| problem solving | problem solving | 13.80% | 7.4% | 5.9% |
| servizio clienti | customer service | 21.60% | 13.2% | 4.3% |
| adattarsi cambiamento | adapt to change | 37.60% | 20.3% | 28.6% |
| comportarsi modo responsabile | behave responsibly | 14.00% | | 5.5% |
| utilizzare computer | use computers | 34.50% | | 3.7% |
| utilizzare microsoft office | use microsoft office | 22.40% | | 3.1% |
| lavorare gruppo | teamwork | 30.50% | | 21.7% |

The skills in Table 3.5 are transversal, as they are even applicable for occupations across skill-levels, but the intensity of demand at each skill-level differs. What stands out is that the demand for any skill that occurs across multiple skill-levels, the intensity is always the strongest for the high-skill level. For instance, creating solutions to problems is a necessary skill in 15.7% of high-skill OJPs, 7.3% of medium-skill OJPs, and 5.6% of low-skill OJPs.

Analysis of the skill-level specific skills which are in high demand but not part of the RTC shows that these skills often belong to widely different types (details can be found in Annex 3.A). For instance, mental skills like analytical thinking and proactive thinking are in high demand for high-skilled occupations, as 10.7% and 10.4% of OJPs ask for them respectively. For medium-skilled occupations on the other hand, 6 different of machine-related skills are in high demand. For instance, installing, inspecting, and maintaining machinery are all asked in 5.4% of OJPs. Two important skills for low-skilled occupations are executing operations in a warehouse and performing warehousing operations, as 8.1% of OJPs and 4.5% of OJPs require these skills. These skills could be related to the demand for the occupation of freight handler, which is one of the more highly demanded low-skilled occupations.

Figure 3.5. Skills for which demand in OJPs exceeds the share of RTC training spots



Note: Only skills that have at least one RTC course and one OJP targeting them are included in the graph. Only the skills for which demand outpaced the training offer are presented.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria.

Combining Figure 3.5 with Table 3.5 shows that the only courses that teach how to use the computer and how to use Microsoft office are courses for medium-skill level occupations, although these skills are in even higher demand for high-skill occupations. The demand for people to know how to use the computer

and Microsoft office for medium-skill occupations relatively high as well, 11.4% and 10.1% of OJPs mention them. And while the share of potential medium-skill participants learning these skills is non-negligible, at 6.5% for both (Panel B), demand still exceeds it. Potentially, there are no courses for high-skill occupations that teach these skills as they are seen as too basic, however, it would be good to investigate whether the high-skilled population actually already is familiar with these skills, given their great importance on the Umbrian labour market.⁹

The number of skills for which the demand outpaces the training offer is largest for high-skill occupations (Figure 3.5 panel A). However, even in this case, there are only eight skills which are offered in the RTC courses, for which the gap between share of OJPs and share of participants is larger than average. The gap is largest for communication, as 9% of OJPs specifically require someone with skills in communication, while just 0.6% of participants are being taught this skill. Again, this might be due to the fact that texts in the OJPs are more general than the texts in the course guides. There might be courses that deal with aspects of communication, but these skills are described in a more specific manner.

In case of the skills for which the training offer exceeds the demand in the OJPs, it holds true for all skill-levels that the RTC is most likely to overly focus on work safety skills, and skills that are formulated in less general terms.

Skills that are the focus of many courses for high-skilled occupations are sometimes closely related to skills that were in high demand but had too few training offers. This is the case for amongst others, digital media/marketing skills. For example, the skills: developing digital content; planning a social media campaign; planning marketing events and promotional campaigns; defining a media communication strategy; elaborating a marketing sales plan; and planning a digital marketing strategy are all much more prominently featured in the RTC than in the OJPs. At the same time, demand for the planning of digital marketing strategies exceeded the share of people learning this skill.¹⁰ It is likely that there is some overlap in the skills as present in the RTC course guides and the skills that are necessary for the OJPs, although the context as described in the OJPs is often more general.

A skill that is particular to courses for medium-skilled occupations seems to be negotiation and contacting commercial relations. Managing negotiation of titles is taught to 13.7% of participants, and carrying out political negotiation, and establishing commercial relations are taught to the same share of participants as well. The demand for these skills in the way they are formulated in the course guides, however, seems to be non-existent.

Some skills that courses for low-skill occupations focus on intensely compared to the demand in OJPs, are food industry related skills. The food skills range from: analysing the characteristics of food products (which has a discrepancy between share of training spots and share of OJPs that is 57 times larger than average), to working independently in the production process for food (discrepancy that is 56 times larger) evaluating the characteristics and quality of food products (discrepancy that is 32 times larger) and preparing things in the oven (discrepancy that is 23 times larger). As discussed in Chapter 1, demand for food industry jobs has increased after the pandemic, which likely would have led to increased demand for food related skills. However, the mismatch can occur either because the demanded skills are described in a different (more general) way in the OJPs, or perhaps the skills for food industry jobs are often implied by the title of the job posting, instead of mentioned in the text. For instance, it is rather self-evident that kitchen helpers and cooks should be aware of how to prepare things in the oven and how to evaluate the quality of their food products.

Lastly, what stands out for low-skilled occupations is that there are no beauty related skills that the RTC focuses excessively on relative to demand on the labour market. This is interesting as there are many courses for beauticians, which coupled with a relatively low demand for this occupation. That the focus is not too intensely on beauty related skills could be an indication that the courses for beauticians are much more general, and often teach transversal skills.

The skill-match between labour demand and training supply for each occupation

This section analyses the alignment between the training provided for each specific occupation and the skill demands for that occupation as they appear in OJPs.¹¹ To assess this alignment, a skill-match score is calculated. This is done by combining two metrics:

- Comparison of the share of skills typically required in a particular occupation (based on OJPs) with the skills taught in each RTC course for that occupation. For example, this metric calculates the percentage of skills taught in the RTC that also appear in the typical demand for a given occupation. The higher the share of skills taught in the RTC relative to the total skills demanded for that occupation in OJPs, the stronger the alignment between the RTC and the OJPs.
- Calculation of the semantic proximity between each pair of skills demanded in an occupation and the corresponding skill taught in the RTC. This metric captures the ‘qualitative’ alignment between the RTC course content, and the specific skill demand expressed in OJPs. For instance, a course devoted to developing the skill to “use using electronic spreadsheets” aligns relatively well with demand for “Excel” skills, but a course in PowerPoint may align less well if the occupation requires specific knowledge of Excel. The analysis using semantic similarity between the keywords describing the course content and those describing the job’s tasks is used to approximate for the alignment between the demand and the supply of skills for each occupation.

Table 3.6¹² presents an example of how the two metrics above are combined at the occupational level to create an indicator of both qualitative and quantitative alignment between the RTC and the demand in OJPs for a specific occupation (in this example “ISCO-7212 Welders and Flamecutters”).

Column 3 lists all the keywords used to describe the typical RTC course for Welders and Flamecutters while column 4 presents the keywords used to describe job’s tasks in the same occupation across OJPs.

The approach followed in Table 3.6 associates each OJPs keyword with one (and only one) RTC keyword picking the combination of RTC-OJPs keywords that has the highest semantic similarity score.¹³ In the example in Table 3.6, for instance, the specific skill demand around knowledge of “Techniques (for) Welding” has been associated with the RTC’s learning goal of developing knowledge related to the use of a “welding electrode”. The semantic similarity between the two set of keywords is high (0.87, see column 6), hinting that the RTC training programmes that target Welders and Flamecutters teaches knowledge related to “welding electrodes” which is in line with the demand of employers of “welding techniques”. Column 5 also show that welding techniques represent a key skill for the occupation as this skill represent 20% of total skill demand for that occupation across all OJPs.

The sum of the share in column 5 is used to create a composite indicator reflecting the “quantitative” alignment of the RTC and the OJPs in the occupation at hand. In the example in Table 3.6, the shaded skills are those that are summed up, as these are the 10 skills that are most closely matched between RTC and OJPs. Summing the shares shows that the RTC course for Welders and Flamecutters ‘covers’ 31% of total number of different skills that are demanded to Welders and Flamecutters across OJPs, so that the quantitative alignment of the RTC’s course content with the labour market demand is modest.

Column 6, instead, approximates for the “qualitative” alignment between the learning goals in RTC and the skills requested by the employers in OJPs. In the example in Table 3.6 the course content (i.e. skills that are taught in the RTC) aligns relatively well with the demand of the employers, with several RTC’s learning goals being semantically close to the keywords mentioned by employers in OJPs for Welders and Flamecutters.

The approach then combines the two sub-indices discussed above in one value for each occupation, where the sum of the values in column 5 (the relevance- how many of the OJPs skills are taught in the RTC) is given a final weight equal to 0.2 and the quality of the alignment of the learning goals (the average of the values in column 6) is given a final weight of 0.8.¹⁴ The final indicator, hence, ranges in between 0 and 1,

with larger values representing a stronger quantitative and qualitative alignment of the RTC course content to the typical demands of employers for the occupation at hand.

For the example in Table 3.6, this means that the total skill-match score is 0.63, as the average similarity score is 0.71, while the sum of the demand for the skills that are shaded is 31%.

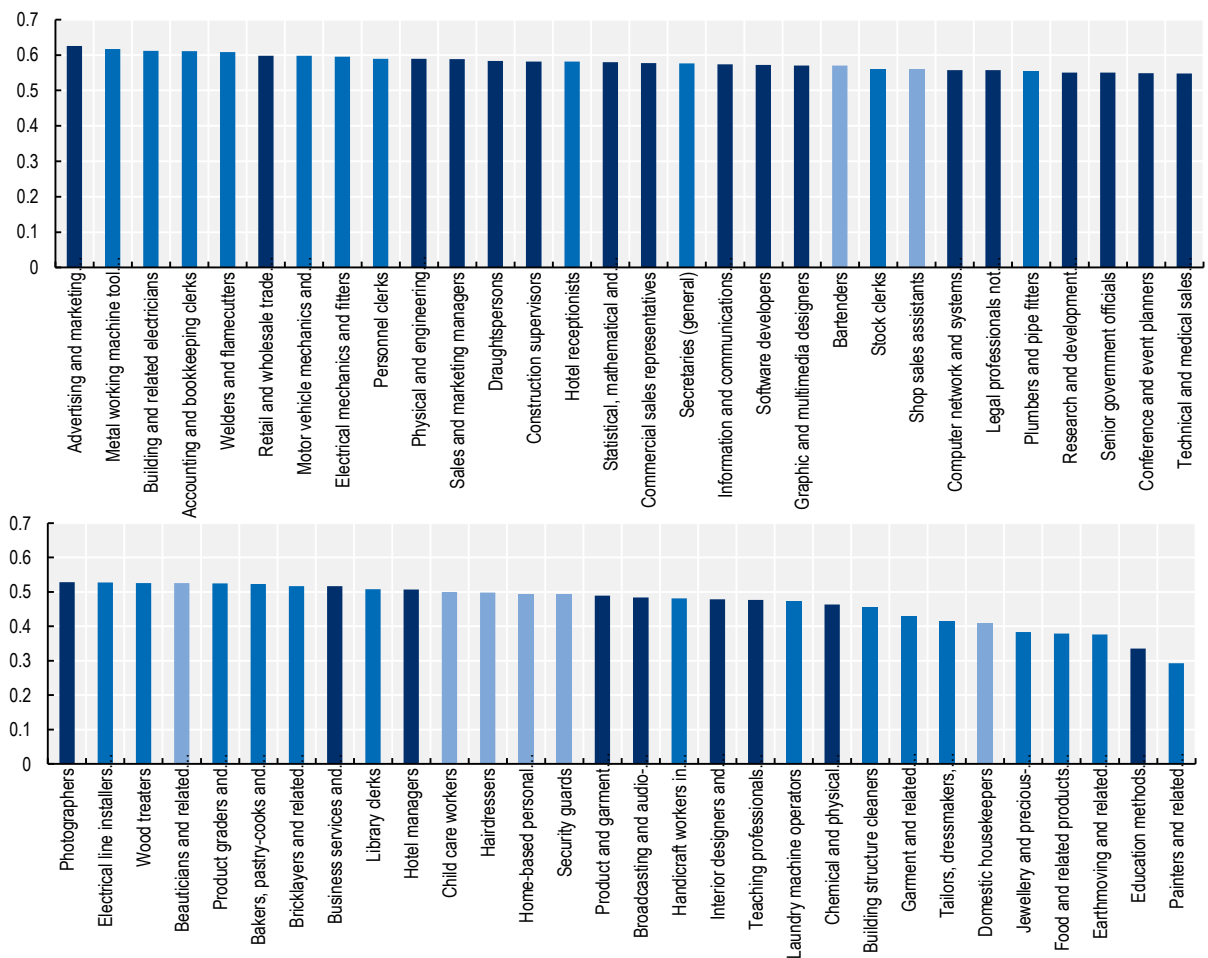
Table 3.6. Example of the skill-match score calculation

| ISCO Code | ISCO name | Skill keywords used in RTC | Skill keywords used in OJPs | Share of skill demanded in OJPs over total skill demand | Keywords similarity between RTC and OJPs skills |
|--------------|--------------------------|--|---|---|---|
| 7212 | Welders and flamecutters | welding electrode | techniques welding (1) | 20% | 0.87 |
| | | prepare materials instrumentation machinery welding | to execute processing metals (2) | 0% | 0.85 |
| | | light drawing technician | use measurement instruments (3) | 2% | 0.84 |
| | | manage documentation reference processing mechanics | use documentation technical (4) | 0% | 0.81 |
| | | evaluate quality operated process productive manufacturing | processes processing machine abrasive (5) | 1% | 0.75 |
| | | cure location work processing | instruments measurement precision (6) | 1% | 0.75 |
| | | to interact resource organization | management project (7) | 0% | 0.69 |
| | | follow measures | to assemble components (8) | 0% | 0.57 |
| | | activity employee or autonomous | creation spirit group (9) | 0% | 0.54 |
| | | measures | drawings technicians (10) | 6% | 0.50 |
| Total scores | | | | 31% | 0.71 |

Note: The RTC provides a longer list of skills than the one presented in this table, including “welding row” and “to interact resource organization building mechanics”. Those skills, however, map into the same OJPs skills as the skills that are presented in the table, convoluting the example. Source: OECD calculations based on Lightcast data and data by ARPAL Umbria.

While the alignment scores in Figure 3.6 are relatively high, the relevance scores contained within them are all rather low. These relatively low relevance scores indicate a mismatch between the skills taught in RTC courses and the skills demanded in the job market at the occupation level. The best alignment (both in terms of quantitative and qualitative scores) is found for Advertising and Marketing professionals, Metal working machine tool settlers and operators and Building and related electricians. For these occupations, the quantity of relevant skills taught in the RTC is higher than the average, meaning that the RTC courses do a relatively better job at providing training that matches the demands of employers both in terms of “quantity” of skills covered and “quality” of the training content. Conversely, the overall alignment between the training provided in the RTC and the skills demands of employers for Earth moving and related plant operators, Education method specialists and Painters and related workers is relatively weaker (see Figure 3.6 panel B).

Figure 3.6. Top and bottom 30 occupations by total alignment score



Note: The darkest blue bars represent high-skill occupations medium blue bars the medium-skill occupations, and light blue bars are low-skilled occupations.

Source: OECD calculations based on Lightcast data and data from ARPAL Umbria. Note: The darkest blue bars represent high-skill occupations medium blue bars the medium-skill occupations, and light blue bars are low-skilled occupations.

Recent training options: The GOL initiative

In March 2022, Umbria’s regional council approved the regional implementation of a national programme that is meant to increase workers’ employability. For the Umbria region, this means that additional training courses are going to be opened in 2023 within the “National programme for the Guarantee of Employability of Workers” (Programma Nazionale per la Garanzia di Occupabilità dei Lavoratori – GOL).

The GOL initiative consists of three different types of courses: reskilling, upskilling and digital skill courses. This subsection discusses the reskilling and digital skills courses in particular. As the courses contained in GOL were not yet part of the Regional Training Catalogue at the moment when the analysis of this report started, it was impossible to systematically assess the alignment of those new courses with the demand expressed in OJPs as it is, instead, done for the RTC. The GOL initiative is, however, a very interesting development in the training options available to individuals in Umbria that merits attention. This is, hence, discussed in this section in a qualitative manner.

GOL programme – Reskilling courses

At the moment of drafting this analysis, the GOL initiative offers 66 reskilling courses, 64 of which are explicitly targeting one or more ISTAT occupations¹⁵ (ARPAL Umbria, 2023_[1]). The courses range from 154 to 575 training hours, with an average length of 254 hours. This means that the reskilling courses in GOL are typically more extensive and detailed learning programmes especially when compared to the average course length in the RTC which was 187 hours.

Preliminary evidence seems to suggest that the GOL initiative is filling some of the gaps in training options by providing new learning opportunities in occupations that are in high demand and for which the RTC training offer was relatively small. In particular, seven highly demanded occupations that were not commonly offered in the RTC will receive new training courses under the GOL initiative.

Among the occupations that are now targeted by new training in the GOL initiative, shop sales assistants, draughtspersons and systems analysts are roles for which the training options in the RTC were falling significantly short relative to the demand expressed in OJPs. Furthermore, the GOL initiative also targets other occupations in high demand with limited to no training options, such as clearing and forwarding agents; kitchen helpers; statistical, finance and insurance clerks, travel consultants and clerks all of which collect approximately 1% of the total OJPs each over the period January 2018 and June 2022.

At the same time, however, the GOL programme still provides training to 12 occupations on which the RTC already focused rather intensely relative to the demand expressed in OJPs. While this new offer focuses on occupations whose demand may be under-estimated by OJPs, some courses are likely to be in excess relative to the demand and may require future modulation, also in light of some of the evidence presented in this report.

As of now, new courses will be provided for motor vehicle mechanics and repairers; cooks; ICT user support technicians; bakers, pastry-cooks and confectionery makers; typists and word processing operators; technical and medical sales professionals (excluding ICT); gardeners, horticultural and nursery growers; web technicians; payroll clerks, and beauticians and related workers. All of these new learning options are therefore for occupations, who have been already heavily targeted in the past by the RTC.

Digital skills in the GOL programme

The digital skills courses in the GOL programme all aim to support individuals develop core digital competencies following the indications contained in the digital competence framework for citizens by the European Commission¹⁶ (Vourikari, Kluzer and Punie, 2022_[2]).

At the moment of drafting this report, the GOL initiative provides training for 67 digital skills courses in the GOL programme (ARPAL Umbria, 2023_[1]), which all have a generally short course duration. The courses are between 15 and 40 hours, with an average of 38.5 hours.

The majority of courses offered by the GOL initiative to improve digital skills cover multiple areas. Among the courses, 50% focus on digital content creation, while 42% teach information and data literacy and communication and collaboration skills. Additionally, around one-third of the courses teach safety related to cybersecurity, but only 11% concentrate on problem-solving skills.

Previous analyses showed that many basic digital skills like using a computer and using Microsoft office are, indeed, in high demand and a clear focus/target in the GOL initiative on digital skills is very much welcome.

In particular, courses related to the first digital competence pillar “information and data literacy”, as well as the third pillar “digital content creation” align particularly well with the observed labour market demands in Umbria. Interestingly, learning goals even explicitly mention some of the specific keywords that are frequently used by employers in OJPs, such as for instance, Microsoft Office. It is important that these

basic digital skills courses encourage people of all three occupational skill-levels to participate, as the demand for these skills was rather high across all skill-levels.

Skills related to data management are also in high demand in the Umbrian OJPs and much of this demand is not met by specific training options in the RTC. Some 5.6% of OJPs analysed in this report, for instance, is looking for people with knowledge and skills related to database management, mostly in high-skill roles. The GOL programme provides some data focused courses to meet this demand.

Developing skills in the area of “communication and digital media” is also a top priority in the new training proposed in the GOL initiative and it aligns well with the skill demands extracted from OJPs which frequently require effective communication skills (mentioned in approximately 7% of OJPs). To put this into context, despite the strong demand, the RTC currently lacks clear options to develop those skills while some 42% of the GOL courses focus on the core competency of “communication and collaboration”.

Finally, training options targeting the development of problem-solving skills are currently under-supplied in the RTC. Figure 3.4 shows, for instance, that approximately 10% of OJPs mention this skill requirement, no training options specifically have learning modules devoted to it. Interestingly, around 11% of the new GOL training options mention developing problem solving skills as an explicit learning goal, highlighting closer alignment of the GOL initiative with the demand of employers in Umbria relative to the existing RTC.

The preliminary analysis of the GOL initiative and of the new courses recently proposed by ARPAL seem to suggest that this initiative could be closing some of the observed gaps between the needs for training and the supply of learning opportunities. Currently, the number of training courses implemented is, however, still limited (as one could expect due to the short life of the initiative). The breadth of the new training options could be extended to capture an even more varied range of skills and occupations, following also the indications contained in this report and the priorities highlighted in the results. Also, the current focus on some occupations, such as beauticians and motor vehicle repairers, seems excessive relative to the observed demand and future revisions of the initiative may decide to shift resource towards providing training for occupations where demand is stronger.

References

- ARPAL Umbria (2023), *Catalogo offerta formativa GOL*, <https://www.arpalumbria.it/catalogo-offerta-formativa-gol> (accessed on April 2023). [1]
- Carnevale, A., T. Jayasundera and D. Repnikov (2014), *Understanding Online Job Ads Data*, Center on Education and the Workforce, <https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech.Web.pdf>. [3]
- Vourikari, R., S. Kluzer and Y. Punie (2022), *DigComp 2.2: The Digital Competence Framework for Citizens - With new examples of knowledge, skills and attitudes*, Publications Office of the European Union, <https://doi.org/10.2760/115376>. [2]

Annex 3.A. Unique skills across skill-levels

Annex Table 3.A.1. Skills that are in high demand that are not offered in the RTC, which are unique in the top 20 highly demanded skills for each skill-level

| Italian name of the skill | Translation of the skill | Skill-level | Share of OJPs |
|------------------------------|--------------------------|-------------|---------------|
| fornire assistenza clienti | provide customer support | H | 24.90% |
| principi lavoro gruppo | group work principles | H | 23.90% |
| software ufficio | office software | H | 14.20% |
| creazione spirito gruppo | group spirit creation | H | 11.70% |
| utilizzare fogli elettronici | use spreadsheets | H | 11.20% |
| database | database | H | 11.00% |
| pensare modo analitico | think analytical way | H | 10.70% |
| guidare gruppo | lead group | H | 10.60% |
| pensare modo proattivo | think proactively | H | 10.40% |
| gestire tempo | manage time | H | 9.70% |
| standard qualità | quality standards | M | 11.00% |
| disegni tecnici | technical drawings | M | 8.00% |
| precision | precision | M | 7.30% |
| machine elettriche | electric cars | M | 6.90% |
| utilizzare sistemi ufficio | use office systems | M | 6.30% |
| funzionalità macchinari | machinery functionality | M | 6.00% |

Notes

¹ There are 72 434 OJPs in Umbria in this timespan.

² This means that training spots for courses such as health and safety, that are not assigned to a particular occupation are disregarded for this analysis. There are 15 548 training spots in this timespan.

³ Notice, however, that previous research has shown that high-skilled occupations are often overrepresented in online job postings (Carnevale, Jayasundera and Repnikov, 2014^[3]). It could be the case that there is more demand for jobs of other skill-levels as well, but that is not visible in the OJPs.

⁴ This implies a discrepancy between the share of OJPs and the share of training spots which is nearly 16 times larger than the average discrepancy in the observed sample.

⁵ The jobs in question are clerical support workers not elsewhere classified, statistical, finance and insurance clerks, travel consultants and clerks, receptionists (general), and general office clerks.

⁶ The two skills in question are `management_relations_clients` which has 3.19% of OJPs, and `establish_relations_commercial`, which is mentioned in 0.34% of OJPs.

⁷ To be able to put more focus on non-work safety related skills, Table 3.4 shows just the highest value of `regulations_safety_firefighting`, `legislation_matter_health_safety_hygiene`, `respect_regulations_safety_work`, `health_safety_place_work`, `legislation_matter_safety_mine`, which would otherwise jointly make up the first five skills in Table 3.4. These five work safety skills are all taught to a share of between 52 and 53% participants of RTC courses.

⁸ Table 3.5 shows just 13 of these skills, and several more can be found in Annex 3.A.

⁹ Basic digital skills are also part of the curriculum of the newly announced GOL programme, which is discussed in a later section. It therefore seems a need for more courses that incorporate digital skills has been spotted. It is important, however, to make sure that people looking to apply for occupations of all skill-levels are made aware of how to perform these tasks.

¹⁰ The algorithm classified `pianificare_strategia_marketing_digitale` and `pianificare_strategie_marketing_digitale` as two different skills, but it can be assumed that these skills are likely very closely related.

¹¹ There are jobs for which there is reasonably high demand, but there are no specific training courses in the RTC. These are jobs like administrative and executive secretaries (2.6% of OJPs), engineering professionals (1.7%), assemblers not elsewhere classified (1.9%), heavy truck and lorry drivers (1.1%), freight handlers (4.4%), and cleaners and helpers in offices, hotels and other establishments (3.3%). These highly demand occupations are not included in the current analysis, as it is impossible to evaluate how well the content of the non-existing courses matches the labour demands.

¹² Table 3.6 is translated to English for presentation purposes, the analysis is always performed on Italian text.

¹³ For more information on the cosine similarity, see Annex A.

¹⁴ The reason why the quality of alignment receives more weight is to balance out the possibility of profession having a much lower total number of skills mentioned in the OJPs.

¹⁵ After mapping the ISTAT occupations to ISCO 4-digit occupations, there are 79 different occupations that are currently targeted in the GOL initiative.

¹⁶ The five digital competencies are: 1) Information and data literacy, 2) Communication and collaboration, 3) Digital content creation, 4) Safety, and 5) Problem solving. The GOL courses do not mention any specific occupations that they are targeting, but they do all mention which digital competency is trained.

Annex A. Creating a mapping between the indicators of the demand and supply of skills: Using machine learning to bridge between the RTC and online job postings

This report uses a dataset of online job postings (OJPs) with monthly information between January of 2018 to June of 2022 to analyse Umbria's labour market trends. The data is collected, transformed and harmonised by Lightcast (formerly Emsi-Burning Glass Technologies). The data is composed of 6.8 million individual level job postings for Italy and 72 434 for Umbria. There are up to 70 different variables ranging from skill keywords contained in each job posting, qualifications and experience required to fill the job and its geographical location, as well as the type of contract (permanent, temporary) and, when available, the salary offered for the specific role advertised. The OECD further transformed the data to create yearly aggregates, cross tabulations and other statistics presented in the document. Furthermore, the raw text of the OJPs is used for analysis, which is explained in this Annex. Lightcast offers the unique possibility to investigate the text contained in each online job posting, which reveals an amount of information that cannot be matched by any other source.

The Regional Training Catalogue (RTC) by ARPAL Umbria contains information on 1649 different courses, that in have 23 652 training spots available. The variables within this dataset have been discussed in Table 2.1 in Chapter 2.

In order to analyse the text information contained in OJPs and in the RTC, this report leverages Natural Language Processing (NLP henceforth) techniques. NLP is a multi-disciplinary field that draws on techniques from computer science, linguistics, mathematics, and psychology. More precisely, NLP focuses on the interaction between human language and computers. It involves developing algorithms and computational models that can process and analyse natural language data, including text, speech, and images. NLP combines computational linguistics—rule-based modeling of human language—with statistical, machine learning, and deep learning models. Together, these technologies enable computers to process human language in the form of text or voice data and to 'understand' its full meaning, complete with the speaker or writer's intent and sentiment (IBM, 2022^[1]). In a nutshell, NLP allows researchers to create a map from words and their complex semantic meanings to numbers that can be analysed through algebraic manipulations and the use of probability models.

This Annex provides technical guidance on the methods that have been used throughout this report to create a mapping between the dictionary of words used in the Regional Training Catalogue (RTC) in Umbria and the skill keywords extracted from online job postings (OJPs).

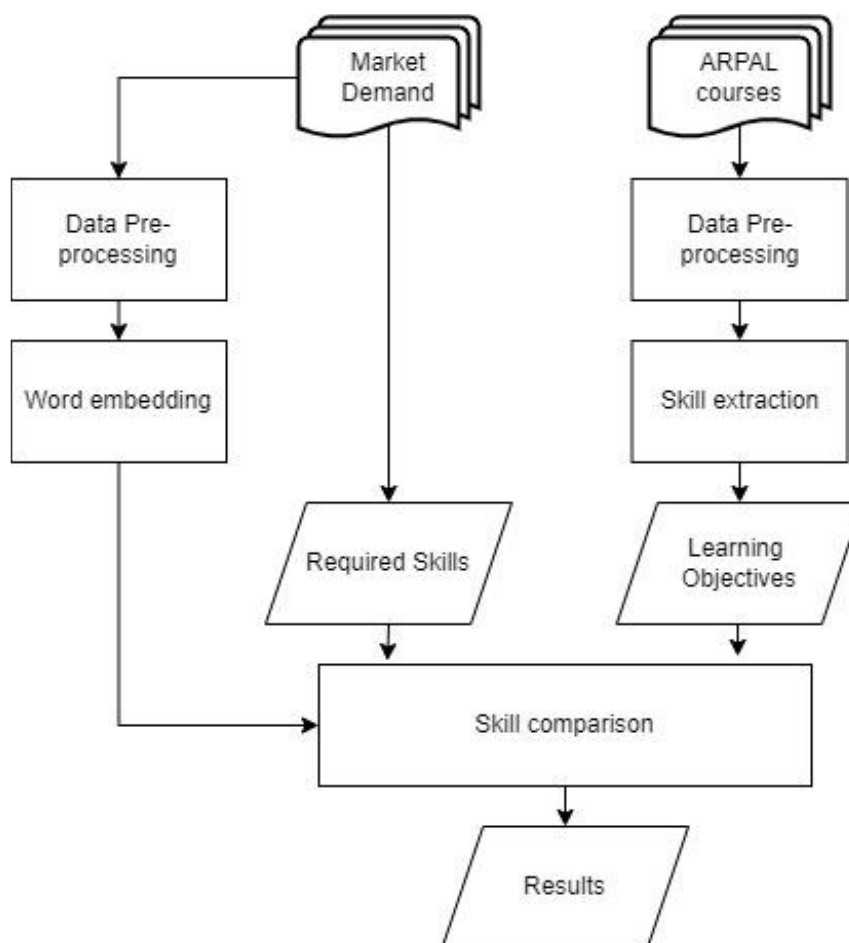
Figure A A.1 provides a graphical description of the conceptual framework adopted to create the mapping between the vocabulary used to describe the training courses in the RTC and the keywords used by employers in OJPs. Both data sources (RTC and OJPs), at the top of the picture, are initially treated as distinct entities, both requiring data pre-processing, that is, standardization of their textual content and the removal of unnecessary words (typically called 'stop words') that do not convey particular semantic meaning or useful information.

The information contained in the RTC comes in separated structured files that contain the description of the learning modules and of the skills that students will learn once enrolling in the course. To highlight the most important aspects of the course descriptions, specific skill keywords have been extracted using simple rules (see Step 1, below).

The OJPs data, on the other hand, is already mapped to the ESCO skill taxonomy when collected by Lightcast and requires minimal pre-processing and cleaning. The keywords extracted from the OJPs are much more abundant than those present in the vocabulary of the RTC as they are derived from the analysis of over a million OJPs gathered for the entire Italian labour market in 2019. These keywords are used to create a semantic representation, the so-called *embedding*, that describes to what extent each skill keyword in the OJPs is semantically associated with another (see Step 2, below).

The embedding created using the OJPs keywords can also be used to determine the extent to which each skill provided by a training program in the RTC is related to a skill mentioned in the OJPs. This is achieved by measuring the semantic similarity (cosine similarity) between the skills in the RTC and those extracted from the OJPs. This strategy allows to mapping each skill keyword in the RTC to a set of skills in the demand side (OJPs), effectively integrating them into the latter's dictionary. This mapping is then used for all subsequent analyses, as presented and described in chapters 2 and 3 of this report.

Figure A A.1. Diagram of the process



At the core of the whole procedure lies the creation of the map or graph: the word embedding. The main computational tool used to create this mapping is *fastText*, an algorithm able to infer a numerical representation of words by means of a prediction task (see Box A A.1). The main advantage of *fastText* is

its focus on subwords, smaller portion of words, that are particularly helpful in creating a more accurate semantic structure for neo-Latin languages, like the Italian language.¹

Box A A.1. FastText: A machine learning approach to the analysis of skill keywords in OJPs and RTC

The current study leverages fastText, an NLP algorithm developed by researchers Bojanowski et al. (2017^[34]). This algorithm creates a mapping between the meaning (i.e. semantics) of subwords contained in text and mathematical vectors, so-called ‘subword vectors’ or ‘embeddings’. Put differently, subword vectors are the mathematical representation of the meaning of the words.

An embedding contains the coordinates and hence the position that each skill has in a high-dimensional vector space, the so-called “graph”. These coordinates make it possible to assess how close or distant every pair of skills are from each other.

As each skill is represented by a vector, the distance between two skills A and B is a measure of vector distance given by the cosine of the angle between the two, the *cosine similarity*:

$$distance(A, B) = \frac{A \cdot B}{\|A\| \|B\|}$$

where the denominator expresses product between the L2-norm (or Euclidean distance) of each n-dimensional vector.

The distance between vectors allows to rank skills from the closest to the farthest. In other words, this approach allows to rank the similarities between every skill vector by estimating their semantic closeness. Using this approach is, therefore, possible to assess whether the skill “Excel” found in the OJPs is semantically (and conceptually) close to “Electronic Spreadsheets”, this latter a keyword found in the RTC.

The remainder of this Annex provides more details about the steps taken to map keywords in the RTC into the skill dictionary extracted from the OJPs.

Step 1: Extracting skills from the RTC

The information contained in the RTC does not conform to a pre-specified dictionary of keywords or a skill taxonomy. Instead, each training programme in the RTC is described by training providers by using words of very different nature and pertaining to a wide range of technical areas. While several of these words provide meaningful information about the course content (e.g. “using electronic spreadsheet”, “baking pastries”, “drawing technical designs”), other words convey little or no information (e.g. “and”, “or”, “even”, “the”).

As the goal is to understand the degree of alignment between the skills provided by the training programs of the RTC and the skill-requirements of the demand side contained in OJPs, **the first step** requires to identify those useful keywords used in the description of each training course that describe the skills, technologies and tasks that are the core of the training programme.

This report uses two variables ‘Competence Unit’ and ‘Learning Unit of Competence’ that describe the course learning objectives (see Chapter 2), after having removed words that convey little information. To focus solely on the skill-related keywords, the text in “Competence Unit” and “Learning Unit of Competence” is broken down into its basic components using a simple rule based on verbs, which separates the sentences into these components. Table A A.1 provides an example of how the text in the

'Competence Unit' and 'Learning Unit of Competence' columns of the RTC is broken down into skill keywords using verbs as delimiters. The training program 20737 is for "Office Automation Operators". In the fourth column, the course description is "handle emails and retrieve information online". The verbs "handle" and "retrieve" are used as skill delimiters, resulting in the extraction of two skills: "handle emails" and "retrieve information online". These two skills are then considered as keywords in the RTC skill dictionary.

Table A A.1. Example of skill extraction

| Training programme | Training programme title | Competence Unit (title of the learning objective) | Learning Unit of Competence (description of the training goals) | Extracted RTC skill |
|--------------------|----------------------------|---|---|--|
| 20737 | Office Automation Operator | Internet and emails | Handle emails and retrieve information online | Handle emails Retrieve information online |

Step 2: Creating the semantic representation

The data provided by Lightcast contain, for each job post, a list of skills required by the employer, identified directly by Lightcast using a variety of different skill taxonomies, including keywords in ESCO. The semantic representation, the word embedding, is created starting from the list of skills of all job postings collected in Italy in the year 2019² and leveraging the CBOW (*continuous bag-of-words*) algorithm (see Box A A.2). This step consists of two parts. Firstly, the list of skills in Italian job posts in 2019 is pre-processed by removing stop words and punctuation. Secondly, the resulting corpus is scanned to match words with a predetermined dictionary of skills, which is composed of RTC skills found in the first step, Lightcast skills provided directly by Lightcast, and ESCO skills.³ The sequence of words that indeed match pre-coded skills coming from these three sources are coded as an *n-gram*.⁴ All words that do not match pre-coded skills, therefore new to the dictionary, are instead selected to create entirely new n-grams; this method allows to expand and enrich the list of pre-determined skills provided by Lightcast. The reason for this choice is to preserve the nuances of the terminology used by training providers in their course descriptions in the RTC and by the employers in OJPs.

For computational reasons only words and bi-grams that appear more than 40 times are kept. It is important to notice, also, that the starting point of the creation of the embeddings is a set of n_grams, representing skills, made by the intersection of three different data sources: the RTC, Lightcast data and ESCO skills.

In the second step, *fastText*,⁵ a python package is used to create the map between words and numbers; this map is technically referred to as word embedding. The algorithm used to do so is the CBOW, better described in Box A A.2.

Before describing the third step it's important to stress that after the second step each skill found in the RTC can be associated to skills coming from the Lightcast and ESCO data, via its cosine similarity described in Box A A.1.

Box A A.2. Continuous bag-of-words (CBOW)

CBOW is the mathematical procedure (technically the model architecture) that fastText implements to construct the semantic representation of skills. The advantage of using fastText over other algorithms is that it allows to focus on subwords. For instance, the skill “realizzare_prodotti_pasticceria” (English translation: “Making pastry products”) can be further decomposed into smaller windows of, for example, 3 characters, as follows:

[“rea”, “eal”, “ali”, “liz”, “izz”, “zza”, “zar”, “are”, “re_”, “e_p”, “pr”, “pro”, “rod”, “odo”, “dot”, “ott”, “tti”, “ti”, “i_p”, “_pa”, “pas”, “ast”, “sti”, “tic”, “icc”, “cce”, “cer”, “eri”, “ria”].

During training, that is, during the phase where the algorithm learns the mathematical representation of the skills, the embedding vectors are learned by the model to capture the semantic and syntactic meaning of each of the subwords. The result is that each of the 29 subwords above will be associated with an embedding vector. For example, the embedding vector for the subword “rea” might look like:

[0.25, -0.33, 0.10, 0.75, -0.05, 0.12, -0.01, 0.07, 0.42, -0.18].

A vector of dimension ten, in this particular example. The original skill, “realizzare_prodotti_pasticceria” will be represented as 29 vectors of dimension 10, each associated to the specific subwords that make up the skill. FastText will repeat the same refined representation of words into subwords, for each skill present in the dictionary.

Whenever fastText will attempt to understand the meaning of the skill “realizzare_prodotti_pasticceria” on the basis of its context, that is, of the skills that surround it in job posts, it will use as input not the skills themselves but their subwords embeddings, adding a level of refinement that is particularly suited for the analysis of neo-latin languages.

The number of skills that define the context, and the dimensionality of the vector that represents each skill, are chosen ex-ante and set, in this case, to 100.

Step 3: Creating a mapping between keywords in the RTC and the OJPs

Each RTC skill found in step 1 is matched with up to five of the most correlated Lightcast skills that share a minimum threshold of cosine similarity of 0.7 with the RTC skill. Table A A.2 and Table A A.3 give for two skills found in the RTC (in the first step) the four and five most similar skills found in Lightcast and ESCO. In the first example, the RTC skill reads “diagnosis_energetic_buildings” and it’s matched with four Lightcast skills: “efficiency_energetic_buildings”, “security_industrial_buildings”, “renovation_system_buildings” and “technology_monitoring_system_building”. The cosine similarity between the RTC skill and the four Lightcast skills spans from 0.81 to 0.7. Despite the possibility of having up to five Lightcast skills associated with an RTC skills the fifth highest match had a similarity below 0.7, and hence was not considered.

The second example instead, shows a case in which five Lightcast skills are matched with the RTC skill “make_products_pastry”. The five skills are “prepare_products_pastry”, “make_products_pastry_base_chocolate”, “being_machinery_products_pastryshop”, “prepare_products_bakery” and “decorate_products_pastry_events_special”. All five Lightcast skills share a similarity above 0.7 with the RTC skill, spanning from 0.91 to 0.79.

Table A A.2. Example (1/2) of RTC – Lightcast/ESCO most similar match

| RTC skill | Lightcast/ESCO skill | Cosine Similarity |
|-----------------------------|--|-------------------|
| diagnosi_energetica_edifici | rendimento_energetico_edifici | 0.81 |
| | sicurezza_edifici_industriali | 0.75 |
| | ristrutturare_impianti_edifici | 0.7 |
| | tecnologica_monitoraggio_impianti_edificio | 0.7 |

Table A A.3. Example (2/2) of RTC – Lightcast/ESCO most similar match

| RTC skill | Lightcast/ESCO skill | Cosine Similarity |
|---------------------------------|---|-------------------|
| realizzare_prodotti_pasticceria | preparare_prodotti_pasticceria | 0.91 |
| | realizzare_prodotti_pasticceria_base_cioccolato | 0.85 |
| | essere_apparecchiature_prodotti_pasticceria | 0.83 |
| | preparare_prodotti_panetteria | 0.81 |
| | decorare_prodotti_pasticceria_eventi_speciali | 0.79 |

The mapping from skill keywords found in one corpus of text to another is, hence, built using similarity measures to match skills by their semantic proximity to each other in the skill space. This is to say that, if two skills have a similar meaning, they are also found closer to each other in the embedding and in the graph (i.e. the vector space). Such mapping allows the analysis to bridge between the dictionary of keywords in the OJPs with those used in the RTC, de facto allowing to create indicators of the alignment of the training offer with the demand of employers in the local labour market.

The accuracy of the mapping was checked by manually examining the most relevant RTC skills and their five most similar Lightcast skills to ensure they made sense together. Any mismatches were flagged and corrected. In particular, the most relevant RTC skills⁶ were manually checked. In order to refine the incorrect associations, data trained and classified on the Italian version of Wikipedia⁷ were used to suggest feasible alternative matches.

Table A A.4 presents an example of an initially mismatched pair of terms and the proposed replacement by a alternative suggestion. The two RTC skills to be matched in this case were “evaluate_quality_productive_process_breeding” and “evaluate_quality_productive_process_baking” both wrongly associated with the Lightcast skill “evaluate_quality_productive_process_pharmaceutical”. While the skill is related to evaluate the productive process, it refers to clearly different context. The suggestion of the general-embedding model in this case was to opt for, unsurprisingly, a more general description of both skill, “analyze_productive_process_improve”, shown in the last column.

Table A A.4. Example (2/2) of RTC – Lightcast/ESCO wrong match replaced with a different skill

| RTC skill | Removed Lightcast Skill | New match |
|--|---|--|
| valutare_qualità_processo_produttivo_allevamento | valutare_processo_produzione_farmaceutico | analizzare_processi_produttivi_migliorarli |
| valutare_qualità_processo_produttivo_panificazione | valutare_processo_produzione_farmaceutico | analizzare_processi_produttivi_migliorarli |

Step 4: K-means clustering

In an additional step, a cluster analysis is carried out using a k-means algorithm with each element of the embedding vectors as a feature for the Lightcast skill classification. This helps to simplify the large amount

of data and identify main areas of skill categories. To describe each cluster, two features are used: the most commonly occurring words in each cluster and the skill that is at the centre of the cluster, which is used to give the cluster a name.

Table A A.5 and Table A A.6 display an example of the cluster assigned by the k-means algorithm to the same skills shown in Table A A.2 and Table A A.3. It is important to stress that RTC skills are less numerous and typically more generic than Lightcast skills and, therefore, they can be mapped (See step 3) to up to 5 different Lightcast skills. Each Lightcast skills, however, is mapped to one (and only one) cluster, but the corresponding RTC keyword (being broader in meaning) can be mapped to one or more clusters. In Table A A.5, for instance, each Lightcast skill is assigned to the same cluster “Technical knowledge in the design and installation of air conditioning systems”. In the second example (Table A A.6), instead, the RTC keyword is mapped to Lightcast skills that fall into two different clusters.

The data-driven clustering was finally also checked manually. In particular, this led to the clusters “Art, cinema and writing”, “Aesthetics” and “Skills in management of vehicles and mobile machinery” all initially grouped into one cluster to be regrouped into three different classes of skills.

Table A A.5. Example (1/2) of RTC – Cluster association

| RTC skill | Lightcast/ESCO skill | Cosine Similarity | Cluster Name |
|-----------------------------|--|-------------------|--|
| diagnosi_energetica_edifici | rendimento_energetico_edifici | 0.81 | Conoscenze tecniche nella progettazione e installazione di sistemi climatici |
| | sicurezza_edifici_industriali | 0.75 | Conoscenze tecniche nella progettazione e installazione di sistemi climatici |
| | ristrutturare_impianti_edifici | 0.7 | Conoscenze tecniche nella progettazione e installazione di sistemi climatici |
| | tecnologica_monitoraggio_impianti_edificio | 0.7 | Conoscenze tecniche nella progettazione e installazione di sistemi climatici |

Table A A.6. Example (2/2) of RTC– Cluster association

| RTC skill | Lightcast/ESCO skill | Cosine Similarity | Cluster Name |
|---------------------------------|---|-------------------|---|
| realizzare_prodotti_pasticceria | rendimento_energetico_edifici | 0.91 | Competenze nella ristorazione e preparazione alimenti |
| | realizzare_prodotti_pasticceria_base_cioccolato | 0.85 | Conoscenze tecniche nella produzione del settore alimentare, tessile e della moda |
| | essere_apparecchiature_prodotti_pasticceria | 0.83 | Conoscenze tecniche nella produzione del settore alimentare, tessile e della moda |
| | preparare_prodotti_panetteria | 0.81 | Competenze nella ristorazione e preparazione alimenti |
| | decorare_prodotti_pasticceria_eventi_speciali | 0.79 | Competenze nella ristorazione e preparazione alimenti |

Reference

IBM (2022), *What is natural language processing?*, <https://www.ibm.com/topics/natural-language-processing> (accessed on April 2023). [1]

Notes

¹ As noticed by the creators of *fastText* other techniques “[...] ignore the internal structure of words, which is an important limitation for morphologically rich languages [...]. For example, in French or Spanish, most verbs have more than forty different inflected forms” (paper link <https://arxiv.org/pdf/1607.04606.pdf>).

² The number of OJPs in 2019 in Italy is 1 308 156.

³ downloaded from https://esco.ec.europa.eu/it/classification/skill_main.

⁴ An n-gram is a series of words concatenated and considered as a unique term. A general example is “new” and “york” usually collapsed in the bi-gram “new_york”.

⁵ *fastText* documentation is available at <https://fasttext.cc/docs/en/python-module.html>.

⁶ That is, those skills that appeared in the RTC’s training programs descriptions with a frequency higher than 30.

⁷ In greater detail, the third step was repeated using, again, a *fastText* model algorithm but this time already trained with Italian Wikipedia data with the intent of giving the numerical representation of words a more general domain of reference. The pre-trained model used is hosted at source: <https://fasttext.cc/docs/en/crawl-vectors.html>.

Big Data Intelligence on Skills Demand and Training in Umbria

The COVID-19 pandemic had a severe impact on the Umbrian economy, and despite recovery of labour demand, the region faces challenges related to digitalisation, tight labour markets, and volatile demand for low-skilled jobs. To address these issues, the OECD and the Umbrian regional agency for active labour market policies (ARPAL) have collaborated to investigate the labour and skills demand of the region using big data techniques applied to online job postings. This report provides new insights into the alignment between labour and skills demand and the training options available in the training and education programmes contained in the Umbrian Regional Training Catalogue. This report builds new indicators to measure the alignment of course content with employer demands in Umbria, with results showing that alignment is relatively good for some occupations but that this can be strengthened to provide job seekers with up-to-date training options that match the demand of the labour market.

