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Skill Needs among European Workers in Knowledge Production and Transfer Occupations

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Abstract: Skills needed in jobs and skills mismatches are important topics for research and policy in the field of economic development and the labour market. Understanding skill needs is essential for improving education and training policies, as labour markets experience dynamic transformation driven by rapid technological progress and increased complexity of work. On the other hand, knowledge economy is considered an important driver force of economic growth. This paper aims to assess skill needs in knowledge production and transfer occupations. We analyse data from online job advertisements and from the European Skills and Jobs Survey in order to provide a comprehensive picture of skills needed in occupations related to science, technology and ICT, as well as teaching positions from higher education in Europe. We find that workers involved in knowledge production and transfer activate in highly changing and challenging working environments. They differentiate themselves by other professionals and technicians mostly by the increased need for ICT skills, problem-solving, communication and learning skills, the ability to collaborate and adaptability. Our results are relevant for designing better education and training programs targeting occupations supporting knowledge production and transfer.

Keywords: knowledge economy; digital economy; knowledge management; knowledge transfer; skills need; high skilled workers

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1. Introduction

The skills forecast for 2030 highlights an expected increase in employment for high skilled jobs, such as managers, legislators, senior officials, professionals, technicians and other positions associated with professionals [1,2]. The number of high qualification jobs is expected to grow at the expense of those with low qualification; the demand for medium qualification is expected to remain fairly stable and the highest number of new jobs will be for professionals [2]. Moreover, macro trends, such as globalisation, accelerated technological change, climate change, instability and social risks, fuel important disruptions in the labour market, increasing the importance of atypical forms of work and bringing significant changes in the nature of performed work. In addition, changes induced by the pandemic have the potential to become structural, including the drop in working hours, increase in remote and temporary work and wage disparities as well as widening of the digital divide [3]. In the context of important macroeconomic shifts to the technologized domains and other dynamic transformations in the labour market, the topic of skills needed and skills mismatches on the labour market grows in importance.

Skill needs reflect the demand for particular types of knowledge and skills existing in economies, sectors and occupations [4]. One aspect of skill needs is given by skills mismatches found when the level or type of skills available does not correspond to existing needs. Skill mismatch can be analysed at individual, enterprise, sectoral and economy levels, consisting of a surplus or a lack of knowledge and competencies [4].

On the other hand, the knowledge economy is a key element of the modern world and relies extensively on innovation and advancements in education and science, as it supports the creation and transfer of knowledge [5]. The knowledge economy is considered an important driving force of economic growth [6,7]. For the further development of the knowledge economy, it is essential that the skill supply matches the demands and challenges involved in the 4th industrial revolution [8]. Knowledge is produced, improved and shared through the collaboration, social process and cognitive processes of individuals, such as reflection [9]. Previous studies have been more focused on disentangling the processes and mechanisms involved in knowledge creation and transfer [10,11] and less on which skills and competences are needed in this respect. However, preparing future and current workers for knowledge management becomes of crucial importance [12], with a special view on providing skills for knowledge creation and transfer. According to OECD, supplying the labour force with high levels of education is necessary but not sufficient in order to support the knowledge economy development. Still, more research is needed in order to inform education policy makers with respect to which skills are needed for the knowledge economy [13].

Our study brings together two important areas of research: skills need in an increasingly changing labour market and knowledge creation and transfer. We consider that the labour market relevant for knowledge creation and transfer is mainly represented by knowledge-rich jobs, such as teaching positions in higher education and jobs in science, technology and ICT (researchers, engineering, ICT workers, technicians in science and engineering). Thus, this paper aims to assess skill needs in knowledge production and transfer occupations. We analyse data from Skills-OVATE and European skills and jobs survey (Wave 1) in order to provide a comprehensive picture of skills needed in occupations related to science, technology and ICT, as well as teaching positions in Europe. Our results are relevant for designing better education and training programs targeting occupations supporting knowledge production and transfer in the European labour market.

2. Literature Review

Worldwide, economies have moved into the Information Age. The new model of the employee working in the current labour market is equipped with competences that are built on knowledge, skills and attitudes, with problem solving and motivation playing important roles [14]. This is why the knowledge management and the knowledge transfer have become very important in the process of education and skills formation. Liyanage et al. [15] describes a process model of knowledge transfer in six steps, while the process could be simplified if the source and receptor have a grade of similarity. Universities are representative environments for knowledge transfer, as their activity is an explicit transfer of knowledge from professors to students, with implicit knowledge transfer being overshadowed but should be encouraged [16].

One of the most important channels of knowledge transfer is the usage of the research results obtained in universities by companies or other organizations, but the first step is to create the link between the universities and their potential beneficiaries [17–20]. A network to facilitate the creation and development of the education–work eco-system is needed to better understand the need for skills and to stimulate proper knowledge transfer [21]. Universities are using various models of knowledge transfer, being considered dedicated organizations for knowledge production and transfer [22–24], even if they are competing for research funds within the research institutes and benefiting from knowledge transfer from industry. The COVID-19 vaccine can be used as the best example of knowledge transfer for large scale production [25].

People interact and more easily facilitate knowledge transfer than organizations, internal transfer has an advantage in comparison to external transfer and reservoirs and networks are its vehicles [26–29]. Knowledge production in the academic versus production environment has similarities but also differences [30], with the networks of all stakeholders contributing to homogenize them.

With respect to knowledge production and transfer, we expect the concept to be clear and properly used. The study of Thompson et al. [31] concluded that for the five roles studied (opinion leader, facilitator, champion, linking agent and change agent) there are inconsistencies and confusions in use, but they appreciate the similarities and suggested the bridge building. At the same time, it seems that the knowledge transfer and knowledge sharing also have similar but different meanings; the level and consistence of the transfer being the main difference and the confusion is related to the information, data and knowledge of conceptual ambiguities or improper usage [32]. Knowledge barriers were added to the previous analysis, being linked with both knowledge transfer and sharing and generally considered in terms of the failure of the process or the factor that blocks the process, which is often more related to a lack of education [32–34].

Chen et al. [35] consider knowledge transfer to be an accelerator of learning and proposed a neural net2net model, Jacobian matching model or other types of networks [36–40]. Knowledge transfer has been valued in the last few years for cross-domain transposition [41,42], with open science offering an opportunity for the increased access to literature, data, tools, etc. There is an increased interest in stimulating knowledge transfer and its positive effects in regard to performances, as well as the factors that influence it [43,44]. Thomas Duve [45], in the first chapter of his book, presents, in detail, the evolution of the School of Salamanca as a dedicated organization to producing knowledge, he describes the mechanism and the mixture that are involved in this co-creation process. A perspective on knowledge production in Arab world is given by Hanafi and Arvanitis [46], who analyse the dynamics of scientific research using the knowledge index [47].

Knowledge production and transfer occupations have a large international base and the skills needed should comply with the mainstream, as reflected in publications [48]. The international scale of knowledge transfer is influencing organization performance and culture and is related to employee retention [49]. In our opinion, employee volatility is higher than in other sectors and knowledge transfer opportunities could influence the decision of highly skilled professionals in accepting a job or a long-term commitment.

A new dimension of the globalization of knowledge production is the trans-disciplinary coproduction, involving different domains and various regions, allowing the shifting of the methods between actors [50,51]. Mixed teams with diverse knowledge are the suggested strategy for companies to stimulate innovation and the co-creation of knowledge in partnership between the research and practice [52–55].

There are opinions regarding the monopoly of very well ranked US and UK journals attracting the main knowledge production and the Anglicisation of knowledge production and transfer occupation [56], as very good skills in English are becoming a necessity for these positions.

Digitalization is the new engine of knowledge production and transfer [57,58], generating the premise of the job delocalization and developing digital skills are now compulsory for new generations [59].

In a recent work by Philipson [60], the analysis of the knowledge production and transfer of phenotypes synthetizes the needs, consequences, transformational and embodied knowledge for the 10 identified typologies.

Defining the skill needs for knowledge production and transfer occupations is a prerequisite condition for quality scientific research and engaging in the knowledge economy which has to answer the challenges of the society [61–65]. The gap between the required and acquired skills should be as small as possible, in accordance with the knowledge and skills needed by the current knowledge economy and Industry 4.0. [66,67]. Previous research showed that three elements of knowledge and skill are essentially contributing to innovation and knowledge production, namely problem solving, communication and beneficiary involvement [68], and teamwork abilities could be also added.

3. Methodology

First, the need to adopt new competences and to perform the work autonomously are important proxies for the skill needs of workers. Exposure to learning new things and work autonomy are relevant non-economic characteristics of jobs that characterise some working environments more than others. They are among the aspects that are taken into consideration when assessing the job strain incidence that is reflected by situations with high job demands and low job resources [69]. Hence, our first research question is:

RQ1: *Are the working environments of knowledge production and transfer jobs characterised by learning new things and by autonomous work more than other professionals and technicians?*

Skill needs are reflected by the skill gaps driven by changes in technologies, working methods and practices, products and services, as well as by the incidence of skill mismatch or skills that have to be updated due to changes in the performed work [4]. Thus, the second research question addressed by this study is:

RQ2: *What are the sources for skill gaps that characterise the workers in knowledge production and transfer jobs more than other professionals and technicians?*

Finally, a significant part of the research on recent and expected evolutions of jobs and skills is related to which skills are important for performing specific occupations or job positions. Evidence regarding skill use and demand is very useful for designing better education and training programs that provide the needed skill supply, in this case, for occupations supporting knowledge production and transfer. Our third research question is:

RQ3 : *What skills profiles are required for performing knowledge production and transfer activities?*

Figure 1 presents the conceptual model of this study considering that characteristics of the working environments, such as frequent exposure to learning and work autonomy, and skill gaps and skill profiles required at the workplace reflect skill needs specific for knowledge production and transfer jobs.

We analyse two important sources of data provided by the EU Agency European Centre for the Development of Vocational Training (CEDEFOP) [70]. First, we analyse data reflecting the supply side from the European skills and jobs survey ESJ (Wave 1). Data were collected in 2014 from 48676 adult employees in the 28 EU Member States. The survey examined the skill needs in occupational and sectoral profiles, as well as skill mismatches driven by changing technologies.

In order to explore skills needed in knowledge production and transfer occupations, we restricted our sample to workers in professional jobs (based on International Standard Classification of Occupations ISCO-08: major group 2) and technician jobs and associate professionals (based on ISCO-08: major group 3). The restricted sample included 17249 adult employees. Furthermore, we focused our analysis on two categories of workers employed in: (1) science, technology and ICT and (2) teaching positions.

In order to answer our research questions, we employed correspondence analysis and logistic regression on the restricted data set in order to provide a comprehensive picture of the working environments and skills needed for performing the targeted occupations.

First, we performed correspondence analysis with the purpose of exploring the association between the analysed occupational categories and the characteristics of the working environments. Correspondence analysis is a data visualisation technique that is very useful for revealing relationship between categories. It allows users to explore similarities between objects (in our case, occupational categories) and their relative relationships with attributes. Thus, we performed two correspondence analyses examining the relation between one variable reflecting three groups of occupations (science, technology and ICT; teaching positions; other professionals and technicians) and two variables measuring the frequency of the following circumstances at work:

- Learning new things
- Choosing the way of performing the work.

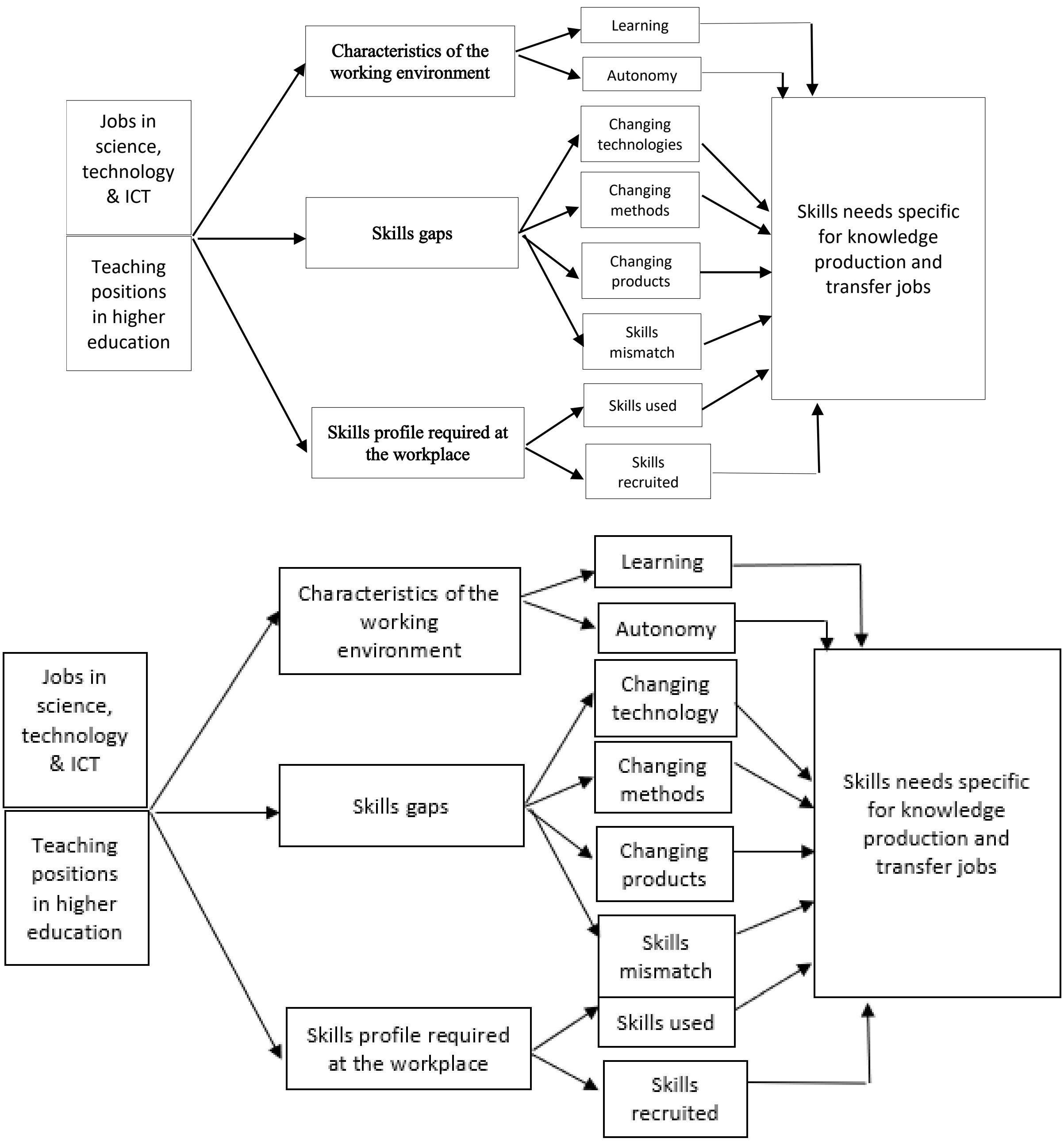

Figure 1. Conceptual model of the research study.

Second, logistic regressions were performed in order to profile targeted occupations from the point of view of skills used at work and skill mismatches. We preferred to construct two different binary logistic regressions for the two occupational categories of interest instead of a multinomial logistic regression, as this approach allowed us to better identify factors that predict the classification into one of the occupational categories of interest. Thus, two models were constructed: Model 1 for science, technology and ICT occupations (the dependent variable takes value 1 for science, technology and ICT occupations and 0 for other professionals and technicians) and Model 2 for teaching positions (the dependent variable takes value 1 for teaching positions and 0 for other professionals and technicians). The independent variables are presented in Table 1.

Table 1. Independent variables included in the logistic regressions.

Items	Variables	Measurement
In the last five years or since you started your main job, have any of these changes taken place in your workplace?	Changes in the used technologies	Dummy variables: 1 = yes, 0 = no
	Changes in the working methods and practices	
	Changes in the products/services delivered	
How important are the following for doing your job?	Advanced literacy skills	Scale from: 0 = Not at all important 5 = Moderately important 10 = Essential
	Advanced numeracy skills	
	Advanced ICT skills	
	Technical skills	
	Communication skills	
	Team-working skills	
	Foreign language skills	
	Customer handling skills	
	Problem solving skills	
	Learning skills	
	Planning and organisation skills	
Overall, how would you best describe your skills in relation to what is required to do your job?	Skills (mis)match	1 = My skills are higher than required by my job 2 = My skills are matched to what is required by my job 3 = Some of my skills are lower than what is required by my job and need to be further developed
Was your main reason for doing training . . . ?	To stay up-to-date with changing skill needs of the job	Dummy variable: 1 = yes, 0 = no

Source of the variables: European skills and jobs survey ESJ (Wave 1) [70].

Additionally, for the third research question, we extracted data reflecting the demand side from Skills-OVATE [71] portal, which provides information on the skills demanded by employers based on online job advertisements (OJAs) collected from EU member states and UK in the past four quarters. Skills-OVATE collects information on the jobs and skills from the millions of OJAs extracted from numerous private job portals, portals of public employment service, recruitment companies' websites and online media. By relying on a huge amount of collected data, the Skills-OVATE system complements the skills intelligence that is based on traditional sources of statistical data. This new source of data provides evidence on labour market trends in real time, offering a way to collect and analyse skills-related data that are not available from other sources [72]. For this paper, data are extracted from online job advertisements posted in 2021 for five occupational groups that we selected as being relevant for knowledge production and transfer activities: researchers and engineers, ICT professionals, science and engineering technicians, ICT technicians and university and higher education teachers.

4. Results

Data collected via the questionnaire-based survey from employees (ESJ) show that teaching positions and science, technology and ICT occupations are more likely to experience the frequent learning of new things than other professionals and technicians. In fact, teaching positions are associated to the highest extent with the permanent learning of new things, while science, technology and ICT occupations are most likely to experience the learning of new things on a regular basis. The visual representation of correspondence analysis suggests that other professionals and technicians experience learning of new things sometimes (Figure 2). The results of the correspondence analysis indicate that occupations relevant to the production and transfer of knowledge, especially the teaching staff, are more exposed to learning new things than other professionals and technicians.

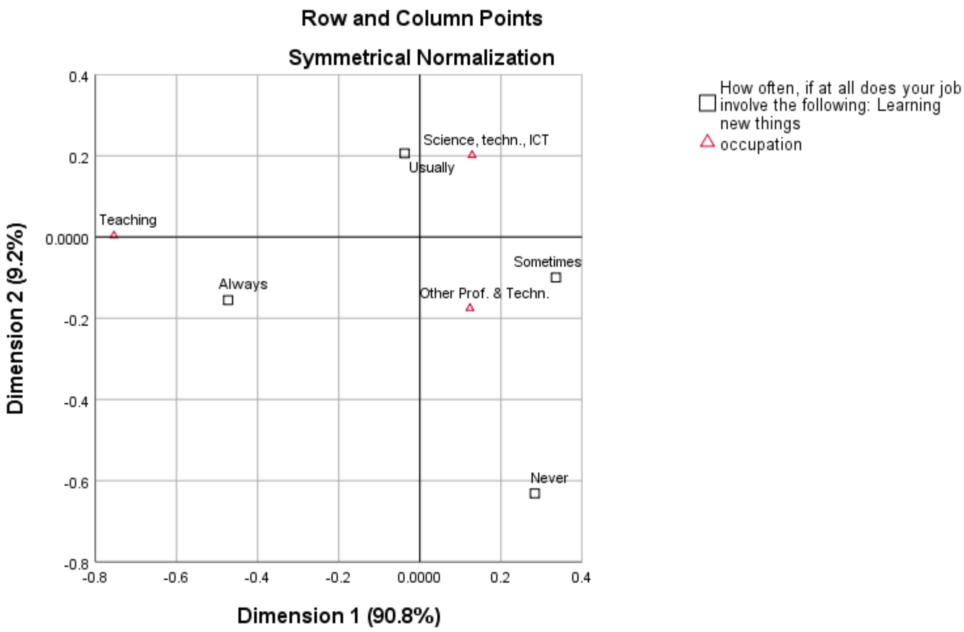

Figure 2. Correspondence analysis between occupation categories and frequency of learning new things at work. Source: authors calculation on data from ESJ (Wave 1) [70].

Figure 3 presents the correspondence analysis between occupational category and the degree of work autonomy. The results show that workers in science, technology and ICT occupations are more those who 'usually' choose the way they do their work, while teaching staff is likely to 'always' make such choices. The other professionals and technicians experience less autonomy at work, compared to the other groups.

The results of logistic regressions for profiling the existing skills needs for targeted occupations are released in Table 2. According to Model 1, science, technology and ICT workers are more likely than other professionals and technicians to experience changes in the technologies they work with. On the other hand, they are less likely to be confronted with changes in working methods and practices. In addition, for science, technology and ICT occupations, advanced ICT skills, technical skills, foreign language skills and problem-solving skills are more likely to be essential than for other professionals and technicians. On the other hand, professionals and technicians for whom advanced literacy and numeracy skills, communication and customer handling skills are more essential, these workers are less likely to be found in science, technology and ICT occupations. Additionally, workers employed in science, technology and ICT occupations have a higher probability than other professionals and technicians of having their skills matched to what is required by their job rather than being higher. Additionally, they have an even higher probability of having lower skills than is required than having a higher skill mismatch. Moreover, workers who participated to training in order to stay up to date with changing the skill needs of the job have higher odds of succeeding in science, technology and ICT occupations than other professionals and technicians.

According to the results of Model 2, teaching staff register a higher probability than other professionals and technicians to experience changes in the working methods and practices they use. On the other hand, they are less likely to confront with changes in the products/services they provide. In addition, professionals and technicians for whom advanced literacy skills, communication and learning skills are more essential are more likely to be found in teaching occupations. On the other hand, professionals and technicians for whom technical skills, team-working, foreign languages and problem-solving skills are more essential are less likely to be found in teaching occupations. Additionally, workers employed in teaching occupations have a lower probability than other professionals and technicians of having their skills matched to what is required by their job with a high skill mismatch. This suggests that workers in teaching positions are more likely to possess skills that are higher than those required by their job than other professionals and technicians.

According to data extracted from a high volume of online job advertisements (OJA) posted in European countries in 2021, occupations related to science, technology and ICT require good knowledge in engineering, manufacturing and construction; knowledge in information and communication technologies; skills in working with computers; as well as communication, collaboration and creativity. In addition, software and applications development and analysis, accessing and analysing digital data and teamwork skills are required for performing such occupations. On the other hand, teaching positions in higher education require communication, collaboration and creativity, knowledge in information and communication technologies and capacity to adapt to changes (Table 3).

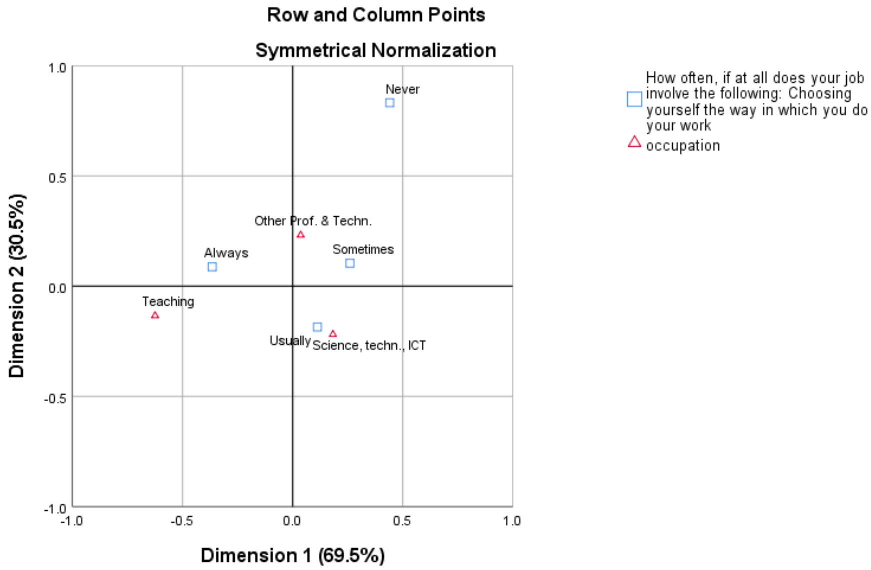

Figure 3. Correspondence analysis between occupation categories and frequency of job autonomy. Source: authors calculation on data from ESJ (Wave 1) [70].

Table 2. Logistic regression for profiling skills needs in science, technology and ICT jobs (Model 1) and teaching positions (Model 2).

	Model 1		**Model 2**	
	Exp(B)	Sig.	Exp(B)	Sig.
Changes to the technologies you use (e.g., machinery, ICT systems) (reference category = No)				
Yes	1.432	0.004	0.868	0.465
Changes to your working methods and practices (e.g., how you are managed or how you work) (reference category = No)				
Yes	0.747	0.019	1.370	0.098
Changes to the products/services you help to produce (reference category = No)				
Yes	1.137	0.305	0.592	0.009
Advanced literacy skills	0.809	0.000	1.221	0.028
Advanced numeracy skills	0.850	0.002	1.111	0.198
Advanced ICT skills	1.365	0.000	0.989	0.894
Technical skills	1.395	0.000	0.749	0.000

Table 2. *Cont.*

	Model 1		Model 2	
	Exp(B)	Sig.	Exp(B)	Sig.
Communication skills	0.734	0.000	1.956	0.000
Team-working skills	1.051	0.374	0.832	0.019
Foreign language skills	1.110	0.000	0.938	0.045
Customer handling skills	0.932	0.012	0.977	0.543
Problem solving skills	1.250	0.002	0.582	0.000
Learning skills	0.917	0.163	1.415	0.001
Planning and organisation skills	0.849	0.005	1.075	0.409
Overall, how would you best describe your skills in relation to what is required to do your job? (reference category = My skills are higher than required by my job)		0.009		0.028
My skills are matched to what is required by my job	1.404	0.004	0.630	0.011
Some of my skills are lower than what is required by my job and need to be further developed	1.639	0.077	0.554	0.170
Training undergone in order to stay up-to-date with changing skill needs of the job (reference category = No)				
Yes	1.506	0.001	0.959	0.832
Constant	0.888	0.813	0.012	0.000

Note: Model 1 Nagelkerke R Square = 0.208, Model 2 Nagelkerke R Square = 0.166. Source: authors' calculation on data from ESJ (Wave 1) [70].

Table 3. Top three skills requested in knowledge production and transfer occupations.

	Level 1 ESCO Skills	Level 3 ESCO Skills
Researchers and engineers	Communication, collaboration and creativity (67.1% of OJA) Working with computers (60% of OJA) Knowledge in engineering, manufacturing and construction (51.9% of OJA)	Personal skills and development (48.9% of OJA) Accessing and analysing digital data (46.9% of OJA) Working in teams (46.4% of OJA)
Science and engineering technicians	Communication, collaboration and creativity (58.7% of OJA) Knowledge in engineering, manufacturing and construction (54.7% of OJA) Working with computers (44.7% of OJA)	Working in teams (36% of OJA) Languages (34.2% of OJA) Accessing and analysing digital data (32% of OJA)
ICT professionals	Working with computers (82% of OJA) Knowledge in information and communication technologies (81.6% of OJA) Communication, collaboration and creativity (81.6% of OJA)	Software and applications development and analysis (73.8% of OJA) Adapt to change (63.6% of OJA) Accessing and analysing digital data (62.1% of OJA)
ICT technicians	Communication, collaboration and creativity (73.2% of OJA) Working with computers (73% of OJA) Knowledge in information and communication technologies (62.6% of OJA)	Adapt to change (62.7% of OJA) Accessing and analysing digital data (50.7% of OJA) Working in teams (47.9% of OJA)
University and higher education teachers	Communication, collaboration and creativity (59.5 % of OJA) Knowledge in generic programmes and qualifications (45.9% of OJA) Knowledge in information and communication technologies (40.4% of OJA)	Adapt to change (60.2% of OJA) Personal skills and development (45.9% of OJA) Working in teams (43.8% of OJA)

Source: data extracted from Skills-OVATE, Data on: Quarter 1 2021–Quarter 4 2021 [71].

5. Discussions

Our results show that working environments related to knowledge creation and transfer are highly demanding as they are more characterised by the frequent exposure of workers to learning new things and by autonomous work, as highlighted by Figures 2 and 3. Such characteristics of a working environment require workers who possess the right mix of abilities and attitudes in order to effectively carry out their tasks. From this point of view, such workers need to be highly adaptable with strong learning abilities in order to possess strong decision-making capacity, motivation, good perceived-self efficacy and self-organisation capacity.

With respect to sources of skill gaps among workers who create or transfer knowledge, technological advancement is one of the main drivers for change in the case of science, technology and ICT jobs, as shown by the empirical results of Model 1 in Table 2. This complements previous findings that indicate that technological change is one of the main determinants of increasing demand for highly educated workers [73]. So, technological advancement induces more than the increased demand in the number of highly skilled workers but also changes the skills they use at the workplace. Results of Model 1 and Model 2 presented in Table 2 indicate that changes affecting the way organisations interact, develop their networks, collaborate and exchange experiences and knowledge represent other sources of change in the skills needed by workers involved in knowledge creation and transfer.

Participation in training for keeping workers up to date with the changing skill needs of the job is more necessary in science, technology and ICT occupations, as highlighted by the results of Model 1 in Table 2. As a result, workers in these jobs are better matched from the point of view of their skills. On the other hand, teachers in higher education are more often over-skilled, suggesting that their potential is not fully used (see results of Model 2 in Table 2).

According to the results of Model 1, with respect to skills that are important in the workplace, science, technology and ICT occupations require more advanced ICT skills, technical skills, foreign languages and problem-solving skills. On the other hand, teaching positions require advanced literacy skills, communication and learning skills to a higher extent (see results of Model 2 in Table 2). These results are consistent with expectations regarding a high growth rate of demand for highly specialized skills [74] and a shift in the labour market towards more autonomy, more ICT and more social and intellectual tasks in the years to come [2]. Our results are consistent with previous conclusions of OECD showing that employers in the knowledge economy rely more on "workplace competencies" as compared with technical skills that refer mostly to cognitive competencies. Workplace competencies include inter-personal skills, such as communication, ability to collaborate, teamwork and leadership, and intra-personal skills, such as ability to learn, problem solving, analytical skills and motivation, as well as ICT skills [13]. Confirming these previous findings, we found that workers involved in knowledge creation and transfer mostly differentiate themselves from other professionals and technicians through the increased need for ICT skills, problem-solving, communication and learning skills, collaboration and adaptability.

The empirical findings of our study clearly demonstrate that the skills of workers in teaching and research need to be higher than for other jobs, and knowledge production and transfer positions have the role of pushing transformation in all socio-economic sectors. On the other hand, we highlighted the consistent importance of digital skills. The main gain and contribution of the present study is an improved knowledge of the skills needed by the most future-oriented jobs, considering that the next generation labour force is educated in this environment. As skills are directly linked with labour productivity, improving skill matches in knowledge-based sectors would boost growth and development. Developing the right mix of skills that respond to the needs of knowledge production and transfer sectors would be highly beneficial for economic and social progress.

Our results contribute to the literature related to the competencies required to participate effectively in the knowledge economy. Improving the understanding of the skill needs is important for updating curricula, developing appropriate actions and providing incentives focused to promote the formation of needed skills. Mapping skills needed by workers of the analysed sectors will help to the design of future digital education meant to address the challenges of the digital transformation and the knowledge economy. Dedicated educational and training programs have to provide strong ICT skills, problem-solving, communication and learning skills, the ability to collaborate and adaptability.

Compared with other studies, our contribution has pointed out and placed the spotlight on workers in knowledge production and transfer, mainly higher education and scientific research, who are considered the spearhead of the evolution of society. Based on our findings, the selection, training, evaluation and promotion of these occupational categories could be reshaped.

6. Conclusions

The expansion of the knowledge economy is changing the landscape of the labour market demands with respect to competences and skills. The demand for workers to perform jobs that involve the production and use of knowledge is increasing and they require specific skills profiles. Occupations related to knowledge production and transfer are more exposed to dynamic transformation than other professionals' and technicians' jobs. Science, technology and ICT workers experience permanent changes in the technologies they use and products and services they deliver, while the teaching staff from higher education faces more changes in the methods and practices they work with. They are more frequently required to learn new things and are in a position to choose the way of performing their work. The participation of workers to training helps them to stay up-to-date and match their skills with changing requirements. Strong ICT skills, problem-solving, communication and learning skills, the ability to collaborate and adaptability are key skills for workers in jobs involving knowledge management. Our findings could be useful for improving the content of both short-term training programs as well as educational programs targeting such jobs. The main limitation of the study is related to difference between the reference periods for the two sources of data. However, results obtained from the two sources are consistent and convergent. Future research could focus on assessing the evolution in the skills needed for jobs in knowledge production and transfer as new comparable data are collected and become available.

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References

1. Cedefop. *Future Skill Needs in Europe: Critical Labour Force Trends*; Cedefop Research Paper No 59; Publications Office of the European Union: Luxembourg, 2016. Available online: https://doi.org/10.2801/56396 (accessed on 23 March 2022).
2. Cedefop; Eurofound. *Skills Forecast: Trends and Challenges to 2030*; Cedefop Reference Series No 108; Publications Office of the European Union: Luxembourg, 2018. Available online: http://data.europa.eu/doi/10.2801/4492 (accessed on 23 March 2022).
3. ILO-International Labour Organization. World Employment and Social Outlook: Trends 2022. Available online: https://www.ilo.org/global/research/global-reports/weso/trends2022/WCMS_834081/lang--en/index.htm (accessed on 23 March 2022).
4. Cedefop. *Terminology of European Education and Training Policy: A Selection of 130 Key Terms*, 2nd ed.; Publications Office of the European Union: Luxembourg, 2014. Available online: https://www.cedefop.europa.eu/en/publications/4117 (accessed on 23 March 2022).
5. Sukharev, O. Measuring the Contribution of the "Knowledge Economy" to the Economic Growth Rate: Comparative Analysis. *J. Knowl. Econ.* **2021**, *12*, 1809–1829. [CrossRef]

6. Barkhordari, S.; Fattahi, M.; Azimi, N.A. The Impact of Knowledge-Based Economy on Growth Performance: Evidence from MENA Countries. *J. Knowl. Econ.* **2019**, *10*, 1168–1182. [CrossRef]
7. Zeb, S. The role of knowledge economy in Asian business. *Future Bus. J.* **2022**, *8*, 1. [CrossRef]
8. Scepanovic, S. The fourth Industrial Revolution and Education. In Proceedings of the 8th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, 10–14 June 2019.
9. Nonaka, I. A dynamic theory of organizational knowledge creation. *Organ. Sci.* **1994**, *5*, 14–37. [CrossRef]
10. Nonaka, I.; Takeuchi, H. The knowledge-creating company: How Japanese companies create the dynamics of innovation. *Int. Bus. Rev.* **1995**, *3*, 337–351. Available online: http://doi.org/10.1016/0969-5931(94)90027-2 (accessed on 5 February 2022). [CrossRef]
11. Takeuchi, H.; Nonaka, I. *Hitotsubashi on Knowledge Management*; John Wiley & Sons: Singapore, 2004.
12. Yu-chu, Y.; Yi-ling, Y.; Yu-Hua, C. From knowledge sharing to knowledge creation: A blended knowledge-management model for improving university students' creativity. *Think. Ski. Creat.* **2012**, *7*, 245–257. [CrossRef]
13. OECD. *Education Policy Analysis 2001*; OECD Publishing: Paris, France, 2001. Available online: https://doi.org/10.1787/epa-2001-en (accessed on 23 March 2022).
14. Bratianu, C.; Hadad, S.; Bejinaru, R. Paradigm shift in business education: A competence-based approach. *Sustainability* **2020**, *12*, 1348. [CrossRef]
15. Liyanage, C.; Ballal, T.; Elhag, T.; Li, Q. Knowledge communication and translation—A knowledge transfer model. *J. Knowl. Manag.* **2009**, *13*, 118–131. Available online: https://centaur.reading.ac.uk/12272/ (accessed on 23 March 2022). [CrossRef]
16. Chugh, R. Do Australian Universities Encourage Tacit Knowledge Transfer? In Proceedings of the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, Lisbon, Portugal, 12–14 November 2015; pp. 128–135. [CrossRef]
17. Agrawal, A.K. University-to-industry knowledge transfer: Literature review and unanswered questions. *Int. J. Manag. Rev.* **2001**, *3*, 285–302. [CrossRef]
18. De Wit-de Vries, E.; Dolfsma, W.A.; van der Windt, H.J.; Gerkema, M.P. Knowledge transfer in university–industry research partnerships: A review. *J. Technol. Transf.* **2019**, *44*, 1236–1255. [CrossRef]
19. Alexander, A.; Martin, D.P.; Manolchev, C.; Miller, K. University–industry collaboration: Using meta-rules to overcome barriers to knowledge transfer. *J. Technol. Transf.* **2020**, *45*, 371–392. [CrossRef]
20. van der Wouden, F.; Rigby, D.L. Co-inventor networks and knowledge production in specialized and diversified cities. *Pap. Reg. Sci.* **2019**, *98*, 1833–1853. [CrossRef]
21. Bertello, A.; Ferraris, A.; De Bernardi, P.; Bertoldi, B. Challenges to open innovation in traditional SMEs: An analysis of pre-competitive projects in university-industry-government collaboration. *Int. Entrep. Manag. J.* **2022**, *18*, 89–104. [CrossRef]
22. Geuna, A.; Muscio, A. The governance of university knowledge transfer: A critical review of the literature. *Minerva* **2009**, *47*, 93–114. [CrossRef]
23. Berbegal-Mirabent, J.; Sánchez García, J.L.; Ribeiro-Soriano, D.E. University–industry partnerships for the provision of R&D services. *J. Bus. Res.* **2015**, *68*, 1407–1413. [CrossRef]
24. Teixeira, S.J.; Veiga, P.M.; Fernandes, C.A. The knowledge transfer and cooperation between universities and enterprises. *Knowl. Manag. Res. Pract.* **2019**, *17*, 449–460. [CrossRef]
25. Price, W.N.; Rai, A.K.; Minssen, T. Knowledge transfer for large-scale vaccine manufacturing. *Science* **2020**, *369*, 912–914. [CrossRef]
26. Argote, L.; Ingram, P. Knowledge transfer: A basis for competitive advantage in firms. *Organ. Behav. Hum. Decis. Processes* **2000**, *82*, 150–169. [CrossRef]
27. Argote, L.; Ingram, P.; Levine, J.M.; Moreland, R.L. Knowledge transfer in organizations: Learning from the experience of others. *Organ. Behav. Hum. Decis. Processes* **2000**, *82*, 1–8. [CrossRef]
28. Fuentes Fuentes, M.D.M.; Ruiz Arroyo, M.; Bojica, A.M.; Fernández Pérez, V. Prior knowledge and social networks in the exploitation of entrepreneurial opportunities. *Int. Entrep. Manag. J.* **2010**, *6*, 481–501. [CrossRef]
29. Prince, M.; Burns, D.; Lu, X.; Winsor, R. Knowledge and skills transfer between MBA and workplace. *J. Workplace Learn.* **2015**, *27*, 207–225. [CrossRef]
30. De Bernardi, P.; Bertello, A.; Forliano, C.; Orlandi, L.B. Beyond the "ivory tower". Comparing academic and non-academic knowledge on social entrepreneurship. *Int. Entrep. Manag. J.* **2022**, *18*, 999–1032. [CrossRef]
31. Thompson, G.N.; Estabrooks, C.A.; Degner, L.F. Clarifying the concepts in knowledge transfer: A literature review. *J. Adv. Nurs.* **2006**, *53*, 691–701. [CrossRef]
32. Paulin, D.; Suneson, K. Knowledge transfer, knowledge sharing and knowledge barriers–three blurry terms in KM. *Lead. Issues Knowl. Manag.* **2015**, *2*, 73.
33. Battistella, C.; De Toni, A.F.; Pillon, R. Inter-organisational technology/knowledge transfer: A framework from critical literature review. *J. Technol. Transf.* **2016**, *41*, 1195–1234. [CrossRef]
34. Yih-Tong Sun, P.; Scott, J.L. An investigation of barriers to knowledge transfer. *J. Knowl. Manag.* **2005**, *9*, 75–90. [CrossRef]
35. Chen, T.; Goodfellow, I.; Shlens, J. Net2net: Accelerating learning via knowledge transfer. *arXiv* **2015**, arXiv:1511.05641.
36. Srinivas, S.; Fleuret, F. Knowledge transfer with jacobian matching. In Proceedings of the International Conference on Machine Learning (PMLR), Stockholm, Sweden, 10–15 July 2018; pp. 4723–4731.

37. Del Chiappa, G.; Baggio, R. Knowledge transfer in smart tourism destinations: Analyzing the effects of a network structure. *J. Destin. Mark. Manag.* **2015**, *4*, 145–150. [CrossRef]
38. Peng, Z.; Li, Z.; Zhang, J.; Li, Y.; Qi, G.J.; Tang, J. Few-shot image recognition with knowledge transfer. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Seoul, Korea, 27–28 October 2019; pp. 441–449.
39. Xie, Q.; Ma, X.; Dai, Z.; Hovy, E. An interpretable knowledge transfer model for knowledge base completion. *arXiv* **2017**, arXiv:1704.05908.
40. Xiao, L.; Xu, S.; Zeng, X. Design and analysis of knowledge transfer in the process of university-industry collaborative innovation based on social network theory. *J. Internet Technol.* **2018**, *19*, 1155–1167.
41. Zheng, H.; Wang, R.; Yang, Y.; Yin, J.; Li, Y.; Li, Y.; Xu, M. Cross-domain fault diagnosis using knowledge transfer strategy: A review. *IEEE Access* **2019**, *7*, 129260–129290. [CrossRef]
42. del Amo, I.F.; Erkoyuncu, J.A.; Roy, R.; Palmarini, R.; Onoufriou, D. A systematic review of Augmented Reality content-related techniques for knowledge transfer in maintenance applications. *Comput. Ind.* **2018**, *103*, 47–71. [CrossRef]
43. Marbun, D.S.; Juliandi, A.; Effendi, S. The Effect of Social Media Culture and Knowledge Transfer on Performance. *Bp. Int. Res. Crit. Inst.-J.* **2020**, *3*, 2513–2520. [CrossRef]
44. Vapnik, V.; Izmailov, R. Learning using privileged information: Similarity control and knowledge transfer. *J. Mach. Learn. Res.* **2015**, *16*, 2023–2049.
45. Duve, T.; Luis Egío, J.; Birr, C. *The School of Salamanca: A Case of Global Knowledge Production*; Brill NIjhoff: Leiden, The Netherlands, 2021; p. 430.
46. Hanafi, S.; Arvanitis, R. *Knowledge Production in the Arab World: The Impossible Promise*; Routledge: London, UK, 2015.
47. World Bank Institute. Knowledge for Development (K4D) Program, Measuring Knowledge in the World's Economies, Knowledge Assessment Methodology and Knowledge Economy Index. 2012. Available online: https://web.worldbank.org/archive/website01030/WEB/IMAGES/KAM_V4.PDF (accessed on 5 February 2022).
48. Gu, Z.; Meng, F.; Farrukh, M. Mapping the research on knowledge transfer: A scientometrics approach. *IEEE Access* **2021**, *9*, 34647–34659. [CrossRef]
49. Ahammad, M.F.; Tarba, S.Y.; Liu, Y.; Glaister, K.W. Knowledge transfer and cross-border acquisition performance: The impact of cultural distance and employee retention. *Int. Bus. Rev.* **2016**, *25*, 66–75. [CrossRef]
50. Simon, D.; Palmer, H.; Riise, J.; Smit, W.; Valencia, S. The challenges of transdisciplinary knowledge production: From unilocal to comparative research. *Environ. Urban.* **2018**, *30*, 481–500. [CrossRef]
51. Metz, A.; Boaz, A.; Robert, G. Co-creative approaches to knowledge production: What next for bridging the research to practice gap? *Evid. Policy* **2019**, *15*, 331–337. [CrossRef]
52. Aggarwal, V.A.; Hsu, D.H.; Wu, A. Organizing knowledge production teams within firms for innovation. *Strategy Sci.* **2020**, *5*, 1–16. [CrossRef]
53. Bauder, H.; Hannan, C.A.; Lujan, O. International experience in the academic field: Knowledge production, symbolic capital, and mobility fetishism. *Popul. Space Place* **2017**, *23*, e2040. [CrossRef]
54. Bender, K. Research–Practice–Collaborations in International Sustainable Development and Knowledge Production: Reflections from a Political-Economic Perspective. *Eur. J. Dev. Res.* **2022**, 1–13. Available online: https://link.springer.com/article/10.1057/s41287-022-00549-7 (accessed on 5 February 2022). [CrossRef]
55. Binz-Scharf, M.C.; Kalish, Y.; Paik, L. Making science: New generations of collaborative knowledge production. *Am. Behav. Sci.* **2015**, *59*, 531–547. [CrossRef]
56. Boussebaa, M.; Tienari, J. Englishization and the politics of knowledge production in management studies. *J. Manag. Inq.* **2021**, *30*, 59–67. [CrossRef]
57. Knudsen, D.R. Elusive boundaries, power relations, and knowledge production: A systematic review of the literature on digitalization in accounting. *Int. J. Account. Inf. Syst.* **2020**, *36*, 100441. [CrossRef]
58. Soler, R.; Peri, P.L.; Bahamonde, H.; Gargaglione, V.; Ormaechea, S.; Herrera, A.H.; Jardon, L.; Lorenzo, C.; Pastur, G.M. Assessing knowledge production for agrosilvopastoral systems in South America. *Rangel. Ecol. Manag.* **2018**, *71*, 637–645. [CrossRef]
59. Lin, L.; Shadiev, R.; Hwang, W.Y.; Shen, S. From knowledge and skills to digital works: An application of design thinking in the information technology course. *Think. Ski. Creat.* **2020**, *36*, 100646. [CrossRef]
60. Philipson, S. Sources of innovation: Consequences for knowledge production and transfer. *J. Innov. Knowl.* **2020**, *5*, 50–58. [CrossRef]
61. Bonde Thylstrup, N.; Flyverbom, M.; Helles, R. Datafied knowledge production: Introduction to the special theme. *Big Data Soc.* **2019**, *6*, 2053951719875985. [CrossRef]
62. Leonelli, S. Locating ethics in data science: Responsibility and accountability in global and distributed knowledge production systems. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2016**, *374*, 20160122. [CrossRef]
63. Muller, J. The future of knowledge and skills in science and technology higher education. *High. Educ.* **2015**, *70*, 409–416. [CrossRef]
64. Blömeke, S.; Busse, A.; Kaiser, G.; König, J.; Suhl, U. The relation between content-specific and general teacher knowledge and skills. *Teach. Teach. Educ.* **2016**, *56*, 35–46. [CrossRef]
65. Kennan, M.A. Data Management: Knowledge and skills required in research, scientific and technical organisations. In Proceedings of the IFLA WLIC 2016—Columbus, OH—Connections. Collaboration. Community, Columbus, OH, USA, 9–19 August 2016. Available online: http://library.ifla.org/id/eprint/1466/ (accessed on 5 February 2022).

66. Stephenson, J. A Systematic Review of the Research on the Knowledge and Skills of Australian Preservice Teachers. *Aust. J. Teach. Educ.* **2018**, *43*, 121–135. [CrossRef]
67. Saniuk, S.; Caganova, D.; Saniuk, A. Knowledge and skills of industrial employees and managerial staff for the industry 4.0 implementation. *Mob. Netw. Appl.* **2021**, 1–11. Available online: https://link.springer.com/article/10.1007/s11036-021-01788-4 (accessed on 17 June 2022). [CrossRef]
68. Sjödin, D. Knowledge processing and ecosystem co-creation for process innovation: Managing joint knowledge processing in process innovation projects. *Int. Entrep. Manag. J.* **2019**, *15*, 135–162. [CrossRef]
69. Cazes, S.; Hijzen, A.; Saint-Martin, A. *Measuring and Assessing Job Quality: The OECD Job Quality Framework*; OECD Social, Employment and Migration Working Papers No. 174; OECD Publishing: Paris, France, 2015. [CrossRef]
70. European Centre for the Development of Vocational Training (Cedefop). Cedefop European Skills and Jobs Survey (ESJS), Wave 1, Spring 2014 [Computer File], 1st ed.; Thessaloniki: Greece. Available online: http://www.cedefop.europa.eu/en/events-andprojects/projects/analysing-skill-mismatch (accessed on 23 March 2022).
71. Skills-OVATE Powered by Cedefop's And Eurostat's Joint Work in the Context of the Web Intelligence Hub. Available online: https://www.cedefop.europa.eu/en/tools/skills-online-vacancies (accessed on 17 June 2022).
72. Cedefop. *Online Job Vacancies and Skills Analysis: A Cedefop Pan-European Approach*; Publications Office of the European Union: Luxembourg, 2019; Available online: http://data.europa.eu/doi/10.2801/097022 (accessed on 23 March 2022).
73. Kiley, M. The Supply of Skilled Labour and Skilled-biased Technological Progress. *Econ. J.* **1999**, *109*, 708–724. [CrossRef]
74. Grigorescu, A.; Sigurdarson, H.T.; Zamfir, A.M. *Foresight Study—2030: Labour Market for Knowledge Production and Transfer*; Editura Universitara: Bucharest, Romania, 2021. [CrossRef]