Research in Higher Education
https://doi.org/10.1007/s11162-024-09816-4

ORIGINAL RESEARCH

Mapping the Occupations of Recent Graduates. The Role of Academic Background in the Digital Era

Helena Corrales-Herrero[1] · **Beatriz Rodríguez-Prado**[1]

Received: 27 July 2022 / Accepted: 6 August 2024

Abstract

The progressive robotisation and the introduction of artificial intelligence imply economic and social changes. In this paper, we investigate their impact on the occupations of recent Spanish graduates and examine how graduates with different skills can expect their occupations to be transformed by the digital era. To this end –using a three-step approach—we first map occupations in terms of the level of the transformative and destructive effects of digitalization, and determine which groups are most threatened. Second, we characterize the technological occupational groups according to dimensions related to worker and job requirements, such as abilities, skills and tasks performed. Finally, we explore the influence of educational background on the probability of belonging to each group. The analysis relies on three data sources—the main one being microdata from the Survey on Labour Market Insertion of University Graduates (EILU-2019)—which provide exhaustive information about students' education and training during and after their degree. Results show that only about 15% of graduates hold jobs that have a high probability of being replaced by machines over the next 10–20 years, although a significant number will still face changes in their occupations that will affect skill requirements. Graduates working in these occupations will need a high level of flexibility if they are to adjust to rapid changes and not be displaced. Moreover, certain features of students' academic background –such as the field of study or more formal education– play a key role and offer some tips to mitigate possible disruptions in graduate employability.

Keywords Occupations · University graduates · Higher education · Digitalization · Automation

✉ Helena Corrales-Herrero
mecorrales@uva.es

Beatriz Rodríguez-Prado
bprado@uva.es

[1] Economics and Public Policy Research Group, Departamento de Economía Aplicada, Universidad de Valladolid, Valladolid, Spain

Introduction

The demand for occupations in developed countries is changing substantially because of technological progress and globalization (Arntz et al., 2016; Bosio & Cristini, 2018; Eurofound, 2008). These structural changes are expected to continue having an impact on employment in the coming years, modifying even further the demand for occupations because new technologies can now penetrate workplaces and societies faster than ever before (González Vázquez et al., 2019a, 2019b). These transformations in occupations also have implications for the qualifications, knowledge, skills, attitudes, and competences that workers need. As a result, they pose major challenges for education and training, both in terms of formal and continuing training and in terms of updating and adapting skills.

One of the most visible and well-established effects of automation is the decline of employment in routine-intensive occupations (Autor & Dorn, 2009; Bosio & Cristini, 2018; Brunello & Wruuck, 2019; Fernández-Macías, 2012; Goos et al., 2014; Oesch & Rodriguez Menes, 2011). Even so, robots are acquiring ever-greater sense and dexterity, which allows them to perform a wider range of tasks. Following an occupation-based approach, Domenech et al. (2018) estimated that 36% of the Spanish labour force are in jobs with a high risk of automation. According to these authors, the potential destruction of jobs is slightly lower than the 47% estimates obtained by Frey and Osborne (2017) for the US, although it is still a formidable prediction.

However, current and future technological changes will not impact all workers equally. The skills workers acquire, and the type of tasks associated with occupations, are key to predicting the risk of being displaced by digitalization (Acemoglu & Autor, 2011; Georgieff & Hyee, 2021; Spitz-Oener, 2006). Workers who perform tasks and use skills that are complementary to technology can benefit from digitalization, whereas those who perform activities and use skills that are easily substitutable by new technologies are more likely to lose their jobs due to automation. In this article, we focus on recent university graduates in Spain, and on those occupations open to them in the labour market, based on the latest Survey on Labour Market Insertion of University Graduates (EILU-2019). As young workers, recent graduates tend to be employed in jobs that are different to those occupied by their more experienced counterparts. Even when they are employed in similar occupations, the tasks they perform could be different (using a different skill set or with different intensity). Graduates are supposed to be skilled workers and are therefore less likely to bear a disproportionate share of the adjustment costs, since the automatability of their occupations is lower in comparison to unskilled workers (Autor & Dorn, 2009; Georgieff & Hyee, 2021). Yet the advance of digitalization might be of greater concern to them given that, as they are just setting out on their professional life, they have less experience and job tenure, and are more mobile across jobs, since they do not yet have significant sunk investment in specific skills (Autor & Dorn, 2009; Fernández Alvaro, 2018; Fossen & Sorgner, 2022). In sum, youth and education may mean that digitalization affects recent graduates differently to the general population. The goal of this study is to identify the extent to which graduates with a range of skills can expect changes in their occupations in the digital age, focusing the analysis on what impact certain academic features will have on the probability of working in occupations that are more exposed to digitalization. More specifically, the paper addresses three research questions: 1. Which graduate occupations are most threatened by digitalization? 2. Which groups of skills and abilities are more relevant for avoiding the destructive effects of digitalization, and 3. What are the generic and specific educational characteristics that make graduates less vulnerable to digitalization?

Our starting point is that new technologies have both destructive and transformative effects (Fossen & Sorgner, 2019). Whereas the destructive effects substitute human labour, the transformative effects modify occupations without necessarily replacing human workers. Most literature measuring the impact of digitalization pays less attention to the transformative effects because earlier waves of technological progress were mainly associated with the automation of routine tasks. However, recent advances in artificial intelligence (AI) mean that non-routine cognitive tasks can also increasingly be automated. In contrast to previous waves of automation, AI might therefore disproportionally affect high-skilled workers, albeit differently (Georgieff & Hyee, 2021). These workers will need to upgrade their skills in order to interact with digital technologies. Given these two forces, the first part of the analysis maps the occupations held by graduates into four groups according to their level of destructive and transformative effects and identifies those which are most threatened by digitalization.

We then analyse the influence of academic background on the probability of belonging to each group. In the context of higher education, academic background refers to the knowledge, skills, experiences, and achievements accumulated by individuals throughout their academic careers. It is important because it reflects a person's level of preparation, experience, and competence in a particular field. The expected connection between the fields of education that universities offer to students and the structure of occupations in the labour market (Salas-Velasco, 2021) suggest that field of education and other aspects –such as language skills or knowledge of new technologies– could have a greater influence on the education-job match and, consequently, on job vulnerability in terms of digitalization. We argue that educational mismatch could also be a relevant factor in getting a job that is more susceptible to digitalization. Additionally, there is the belief that the skills needed for employment are becoming increasingly technology-related (Cesco et al., 2021; González Vázquez et al., 2019a, 2019b; Kornelakis & Petrakaki, 2020) and that they require more training in science, technology, engineering, and maths –the so-called STEM subjects (Wright et al., 2017). In this sense, graduates in fields that provide more occupation-specific skills (specifically in STEM)—as opposed to general skills—are assumed to behave better in their labour market insertion. In sum, the analysis seeks to identify to what extent graduates with different abilities can expect their occupations to be transformed in the digital era.

This paper makes a threefold contribution to the literature. First, to the best of our knowledge, this is the first attempt to measure the impact of digitalization faced by graduates in the occupations offered to them by the labour market. Our classification of occupations according to the two opposing forces of technology (destructive and transformative effects) provides insight into the extent to which graduates will be at risk of technological unemployment in the future. In addition, the inclusion of two different measures of digitalization aims to avoid recent criticism of the Frey & Osborne (2013) proposal. It is argued that their measure overestimates the potential impact of automation, because it neglects the substantial heterogeneity of tasks within occupations as well as the fact that workers adapt their tasks to new technologies (Arntz et al., 2016, 2017). Second, we add to the above classification a more detailed description of the relevant worker and occupational requirements in terms of abilities, skills and tasks that will keep graduates away from the risk of digitalization. This better approximation of job composition offers valuable knowledge for higher education institutions and graduates. Third, although there is empirical literature examining what influence specific graduate characteristics have on different labour market outcomes, such as the probability of finding a job, the wage level, and the quality of the job, this study enhances this body of literature on higher education by examining the risk of digitalization as a labour outcome and by considering various aspects of graduates' academic backgrounds in a comprehensive way. We empirically highlight the important role played by academic background (knowledge, skills, experiences, and achievements accumulated throughout the academic career) in mitigating the risk of digitalization among young graduates. In short, the paper contributes to the scarce empirical literature in higher education that focuses on technological advances and their impact on the graduate labour market by showing which occupations will be most affected, which educational characteristics have the greatest impact, and the importance of skills and competences as society becomes increasingly digital.

The case of Spain is relevant for several reasons. First, according to the OECD Regional Outlook (OECD, 2019), the prevalence of jobs at risk of automation in southern Europe is much higher than the average. While the manufacturing sector is a priori more vulnerable to automation than the services sector—which would make countries with more manufacturing employment more affected– in practice, a particular job may be more susceptible to automation depending on how the work is organized. Differences between countries thus arise from differences in occupational composition and workplace organization rather than sectors (Nedelkoska & Quintini, 2018). Second, Spain has already reached the European 2030 target of raising the tertiary attainment rate to at least 45% of the population aged 25–34. This has risen steadily since the implementation of the Bologna Process and has increased by over ten points since then (52.0% in 2023). However, the oversupply of graduates has not been matched by a corresponding expansion of elite jobs, which has led to fierce competition for existing jobs. In this sense, how higher education institutions will respond to the challenges of the future needs of industry and employment is a key issue.

The rest of the paper is structured as follows. In the next section, we present a brief review of the literature. In "Analytical Approach, Data and Measures" Section, we describe the data set drawn from several sources of information. We also explain which measures are most suited vis-à-vis identifying the impact of digitalization on occupations. "Results" Section shows the results, and finally, "Discussion and Conclusions" Section summarizes the conclusions derived from the research and gives some policy implications.

Theoretical Background

In this section, we review the principal arguments we find in the literature concerning what effects digital technologies have on employment and, more specifically on occupations. We also show how digitalization is evolving in Spain and how it is expected to affect young people. Finally, we review the literature on how technological changes are affecting higher education.

From a theoretical perspective, the impact of digital technologies on employment is ambiguous. On the one hand, economic theory predicts a negative effect in the case of automation-related technologies, since by taking over some of the tasks performed by human workers, the latter are partially or completely displaced (Acemoglu & Restrepo, 2018, 2020; Domenech et al., 2018). Yet digital technologies could also enhance employment through potential cost reductions brought about by automation, which might translate into more demand for goods (or services), leading to an increase in activity. Other positive job-enhancing channels include the creation of jobs in emerging business areas and the creation of new work activities within existing jobs that have a comparative advantage over technologies (Acemoglu & Restrepo, 2019; González Vázquez et al., 2019a, 2019b).

Although the effect in terms of total employment is not yet clear, what does seem more certain is that the composition and distribution by occupations will change (Arnz et al., 2016: Bosio & Cristini, 2018; Eurofond, 2008). For this reason, rather than quantifying the net effect on employment, one strand of the literature has focused on identifying which occupations are more vulnerable to digitalization (González Vázquez et al.,). The main concern is to measure how the different types of digital technologies affect the tasks performed in each occupation. The first contribution in this area corresponds to the work of Frey and Osborne (), who obtained a measure for the probability of automation for each occupation, distinguishing between low risk occupations (less than 30% probability), medium risk (between 30–70%), and high risk (greater than 70% probability) of automation. The occupation-based approach followed by these authors gave an estimation of up to half of the US workforce being at high risk of automation.[1] Arntz et al., (2016, 2017) proposed a task-based approach, since workers within the same occupational group may perform different tasks. In this respect, it is worth mentioning the seminal work of Autor et al. (2003) in which the theoretical concept of occupational tasks is set out, differentiating between the term occupation, which denotes a particular field of work and broadly describes the work performed, and the term task, which refers to the individual activities a worker performs on a regular basis to fulfil work duties at the workplace. The task approach considers that the substitutability between technology and labour does not occur at the occupation level but rather depends on the susceptibility of different tasks to automation and that ignoring this variation leads to an overestimation of the overall risk of automation in the economy. Following this approach, 9% of jobs in Europe were found to be at high risk of being automated.[2] From a different perspective, Felten et al., (2018, 2019) reached similar results taking into consideration that new technologies also have transformative effects on occupations, and which do not necessarily involve machines replacing human workers. Specifically, they developed a measure of advances in artificial intelligence (AI) that they related to skills and occupations—the AI occupational impact measure.[3] Later, Fossen and Sorgner (2019) combined these two measures (risk of automation and advances in AI) considering that occupations differ from each other in terms of what impact digitalization has on them, implying that a given occupation might face different levels of transformative and destructive risks at the same time. Their results revealed that a substantial share of occupations—employing some 38% of the US workforce—face low transformative and high destructive impacts of digitalization, which they categorized as a *Collapsing group*. In a more recent work, Fossen and Sorgner (2022) added a new measure proposed by Brynjolfsson et al. (2018) to capture the impact of new digital technologies on occupations –the suitability for machine learning (SML) measure—which identifies potential labour-displacement technologies. The SML assesses occupations from the perspective of amenability to remote work and the need for human proximity during task execution. McGuinness et al. (2021) propose a unique measure of skills-displacing technological change (SDT) that reflects the erosion or obsolescence of workers' skills based on employees' expectations and experience regarding the influence of technology on

[1] Following the same approach, other authors find a probability of automation that varies between 35 and 60% in Europe (Bowles, 2014; Domenech et al., 2018; Lawrence et al., 2017; Pajarinen & Rouvinen, 2014).

[2] Nedelkoska & Quintini (2018) and Pouliakas (2018) applied variants of this task-based approach, and their results are in line with those of Arntz et al. (2016).

[3] Georgieff & Hyee (2021) adapted the AI occupational impact measure and extended it to 23 OECD countries, matching Labour Force Surveys.

their skills. This contrasts with previous measures that rely on the views of experts. They find that 16% of adult workers in the EU are impacted by SDT.

All of these studies examining the impact of digitalization on the workforce as a whole highlight the existence of a demand for new skills, while others are either being outgrown or seeing their lifespan reduced. In short, the digital revolution has brought with it skill gaps by creating the need for new skills that are not immediately available in the labour market. These trends have put additional pressure on higher education institutions to undertake a more systematic reflection on how to integrate new skills. In this sense, new and deeper technical skills are needed to deal with the latest automation and digital technologies. Nevertheless, soft skills, including social and personal skills, are also becoming increasingly important for handling workplace complexity (Cesco et al., 2021; Kornelakis & Petrakaki, 2020). As a result, more emphasis should be placed on understanding and decision making and less on information acquisition (Lincoln & Kearney, 2019), which means using skills rather than acquiring knowledge.

One key question concerns knowing whether the impact of digitalization affects young workers differently. A priori, young workers have less experience and job tenure, and are more mobile across jobs since they still lack a significant sunk investment in specific skills. For this reason, they could be more easily displaced by digitalization (Domenech et al., 2018; Nedelkoska & Quintini, 2018). On the other hand, high-skilled workers might be less likely to bear the brunt of adjustment costs since the automatability of their jobs is lower when compared to low-skilled workers because their jobs tend to require soft social skills such as cooperation with other employees (negotiation) or spending more time influencing others (persuasion) (Arntz et al., 2016). Some previous empirical studies conclude that university graduates stand out for being employed in occupations with a much lower risk of digitalization than other workers, although there are major differences depending on their field of studies (Domenech et al., 2018). At the same time, however, digitalization primarily affects high-skilled jobs that need to be accompanied by greater provision of training and workplace learning. This is the case of certain jobs, such as those in STEM areas, where graduates enjoy considerably higher starting salaries as they can apply the job-relevant skills they learned at university, and which are subject to rapid changes such that the initial skills become obsolete, forcing them to learn new skills (McGuinness et al., 2021). Furthermore, many highly skilled workers cannot take advantage of their skills due to the low demand for them in the labour market. Educational mismatch is aggravated when investment in technology increases, leading to greater digitalization (Randstad, 2021; Salas-Velasco, 2021). Moreover, digitalization not only renders certain job tasks obsolete but at the same time opens up employment opportunities and facilitates the development of new forms of flexible work, such as mobile work, project work or platform work, which the pandemic accelerated in an effort to reduce reliance on human labour and contact between workers, or to re-shore certain production.

Finally, the process of digitalization affects economies to varying degrees. A priori, Spain is one of the European countries where the threat of automation could be most pronounced, due to its sectoral specialization and to the fact that—within each sector—there is a greater presence of occupations in which the tasks performed are more exposed to automation (OECD, 2019). In this line, the scarce empirical evidence on the impact of digitalization technologies in the Spanish labour market shows that, although the process of job transformation is underway, Spain lags behind other countries in this area (Domenech et al., 2018; Hernández Lahiguera et al., 2020; Lladós-Masllorens (2019)). During the Great Recession, job destruction was mostly concentrated in occupations with a medium or high probability of automation. Subsequent job creation was directed towards occupations that were more poorly positioned vis-à-vis technological progress (Domenech et al., 2018). In contrast to other countries, digital technologies are not driving a task-biased technological change that implies a decreasing demand for workers performing routine tasks. On the contrary, a skill-biased technological change is taking place, although new occupations mostly demand a limited set of complex skills. This is a consequence of the routine task-intensive economic structure in Spain (Lladós-Masllorens, 2019). The predominance of routine (but not repetitive) tasks in many services linked to serving, attending, health and care is limiting the scope of automation. Although routine jobs are predominant, the need for manual skills and the absence of standardization in certain tasks are protecting these jobs, at least temporarily, from being replaced by technology.

The immediate consequence is an increasing polarization of employment opportunities. In addition, a progressive de-skilling effect is emerging, as high-skilled workers move down the occupational ladder. Moreover, a structural shift is taking place in the labour market, with workers reallocating their labour supply from middle-income manufacturing to low-income service occupations. The current trend towards polarization implies an increase in employment in high-income cognitive jobs and low-income manual occupations, accompanied by a hollowing-out of middle-income routine jobs (Goos et al., 2014).

All of these transformations in occupations have implications for the qualifications, knowledge, skills, attitudes, and competences required from workers. Consequently, they pose formidable educational challenges, both in terms of formal and continuing training, and in terms of updating and adapting skills. The Bologna Process, which began over two decades ago, shifted the focus of higher education from content to competences. Today, one of the key objectives of education is to equip students with transferable skills that go beyond the standard approach to fields of study. Moreover, technological developments have led recent literature addressing higher education to focus on the concept of employability skills, with an emphasis on those that prepare graduates for the increasingly complex world of work (Osmani et al., 2015; Suleman, 2018; Kornelakis & Petrakaki, 2020; Cesco et al., 2021). The current labour market requires professionals with flexible and diverse competences who can adapt to the complexity of the work environment and who can develop skills that enhance flexibility of thought and action (Belchior-Rocha et al., 2022). In other words, in recent years, the policy and academic debate concerning the relationship between higher education and the labour market has concentrated on the need to foster graduate employability. There is significant pressure to equip future employees with suitable skills for economic and labour market imperatives (Teichler, 2009). As a result, the employability of graduates has become a new institutional mission of higher education. There are many studies exploring different facets of this issue. Some examine how universities are adapting their curricula and teaching methods to equip students with the skills employers are demanding, including problem solving, team working, communication, information technology, and the ability to improve one's own learning and performance (Akour & Alenezi, 2022; Cesco et al., 2021; Gouda, 2022; Kornelakis & Petrakaki, 2020). One of the most consistent findings is that integrating work into learning process (through practical experiences) can mitigate the impact of technology (Monteiro et al., 2021; Scandurra et al., 2023). Other studies examine the importance of lifelong learning and continuous upgrading of the skills required for graduates to remain competitive in the labour market (Bonfield et al., 2020; Cesco et al., 2021). In addition, some empirical literature examines the influence of specific graduate characteristics on different labour market outcomes, such as the probability of finding a job, wage level, and job quality, defined in terms of stability, working hours, or the risk of over-education (Lauder & Mayhew, 2020). The characteristics analysed include different fields of study (Xu, 2013; García-Aracil, 2008), participation in employability programmes (Bolli et al., 2021; Scandurra et al., 2023), study abroad (Croce & Ghignoni, 2024), socioeconomic background (Tomaszewski et al., 2021), as well as age and gender (Bellas, 2021), among others. Unfortunately, we have not identified any articles that examine the impact of multiple academic characteristics on the risk of being affected by digitalization in a comprehensive way. In this sense, this study enhances the body of literature on higher education by examining the risk of digitalization as a labour outcome and by considering various aspects of graduates' academic background.

Analytical Approach, Data and Measures

Analytical Approach

To address the research questions, that is, which graduate occupations are most threatened by digitalization, which sets of skills and abilities and what specific educational characteristics make graduates less vulnerable to digitalization, our empirical analysis follows several steps. To tackle the first question, we map occupations held by graduates in terms of the destructive and transformative impacts of digitalization, following the proposal of Fossen and Sorgner (2019). To do so, we employ the median of the measures used to capture the destructive and transformative impacts of digitalization in order to avoid the potential influence of extreme values on the average. As a result, we are able to categorize occupations into four technological groups (Human Terrain, Rising Stars, Collapsing group, and Machine Terrain). We then characterize the four occupational groups identified in the first stage according to the skills and abilities associated to graduates' occupations and the task content of the jobs in each technological group. As can be seen in the next section, we draw on the classification of skills, abilities and tasks provided by the Occupational Information Network (O*NET) database compiled by the US Department of Labor and we use descriptive statistics. Finally, we analyse the effects of individuals' academic background on the probability of belonging to each technological occupational group. To do so, since all possible groups are disjoint and the order is irrelevant, the multinomial logit model is the estimation method best suited. This model provides the probability that a graduate with specific characteristics is in each technological group. In this way, the analysis links technological classification of occupations to individual job characteristics and evaluates the role of certain academic factors in determining vulnerability to digitalization.

Data and Measures

The analysis relies upon two levels and several data sources that have been merged, as detailed below. In the first data level, we use graduate microdata from the most recent Survey on Labour Market Insertion of University Graduates (EILU-2019) carried out by the National Institute of Statistics (INE, 2020). In the second level, we link several sources that provide for each occupation a measure of the destructive (automation risk) and transformative (advances in AI) impact of digitalization and the skills, abilities and task content required in each occupation. We merge occupational information with microdata using the job held by each graduate at the moment of the survey. Information about the data level and sources is summarized in Table 1.

Table 1 Data levels, sources and measures

Data level	Data source	Measure
Microdata of individuals (graduates)	Survey on Labour Market Insertion of University Graduates (EILU-2019)	Academic background indicators
		Occupation held by the graduate at the moment of the survey ([a])
Information by occupation	Frey and Osborne (2017) and Fernández Alvaro (2018)	Automation risk by occupation
	Felten et al. (2018)	Advance in artificial intelligence by occupation
	Occupational Information Network (O*NET-November 2019)	Skills, abilities, and tasks by occupation

[a]We merged occupational information and graduate microdata into a single database using the occupation held by graduates at the moment of the survey, in 2019

More specifically, the EILU-2019 provides information for some 30,000 university students who graduated in 2013/2014, and which was collected using both administrative records and a direct survey four years after graduation. We focus the analysis on those who were employed at the moment of the survey, i.e. in 2019, four years after graduation. The sample thus contains 26,994 individuals and, using the weights included in the survey, represents a population of 196,073 graduates. The survey includes exhaustive and retrospective information on education and training completed by students before, during, and after their graduation that allows the detailed individual academic background for entering the labour market to be built.

In particular, the graduate's academic background has been measured by several indicators (see Table 2). First, the field of education—defined as the subject matter taught in an education programme—is an important factor that could determine their chances of digitalization vulnerability. Given that job titles are generally defined in terms of educational requirements that coincide with the level and field of formal education and that some fields of education provide specific skills to graduates that are more difficult to automate, graduates in certain fields are assumed to be less vulnerable to digitalization. We thus consider the *field of education of the degree* by which the individual is selected in the EILU survey. The EILU survey contains information about the usual five main branches of knowledge (Arts and Humanities, Sciences, Social Sciences and Law, Health Sciences, and Engineering and Architecture), and the programmes are also classified into fields of education following the latest classification of fields of education and training in the International Standard Classification of Education (ISCED-F 2013). This resulting variable has ten categories constructed from the variable field of study (see Table 2). From this variable, we construct ten binary variables that take the value 1 for each field of education, and 0 otherwise.

We also focus on other factors related to the degree and, to a large extent, to the field of education. The latest modification of Spanish higher education—adapting academic degrees to the Bologna principles—made *undergraduate internships (curricular or voluntary)* popular for most degrees and strengthened the development of mobility between European universities. In general, the role of internships and *having studied abroad* can be manifold. In studies which examine the transition from university to labour market, one of the most recurrent findings relates to the importance of undertaking practical experience during higher education (Jung, 2022; Scandurra et al., 2023). In particular, lack of work experience is highlighted as a potential transition barrier, especially in fields of study that provide more occupation-specific skills rather than more general skills (Monteiro et al., 2021). In our case, given that the internship is narrowly limited to the field of education, it may have an impact on the vulnerability of digitalization. Studying abroad also represents a peculiar step in students' educational path which, in principle, enlarges and enriches their human capital. This involves attending classes and taking exams in a new and stimulating context in order to foster academic learning. It also allows for the acquisition of a set of non-cognitive skills that are distinct from academic learning; namely, a propensity to international mobility, openness to change, flexibility to adapt to diverse environments, problem solving, and the ability to interact (Croce & Ghignoni, 2024). In any case, both factors can be a door to a first job, generate additional competences, enrich social networks and so on (Di Meglio et al., 2022). In Spain, the high youth unemployment rate has stimulated the role of this first work experience among graduates and participation in the Erasmus programme.

The survey also collects information on the number and level of *languages graduates know in addition to their mother tongue*, as well as their ability to use computers and other devices. For language skills, we distinguish between graduates who speak one or more

Table 2 Definition of the variables and the stages at which they are used

Variables	Type of variable	Categories
Stage 1. Generating technological groups of occupations		
Destructive impact of digitalization (risk of automation)	Numeric	
Transformative impact of digitalization (Advances in AI)	Numeric	
Stage 2. Characterizing technological occupational groups		
Abilities	17 Ordinal variables	Cognitive (memory, attentiveness, verbal, reasoning, quantitative, perceptual and spatial abilities); Psychomotor (fine manipulative, control movement abilities and reaction time and speed); Physical (physical strength, endurance; flexibility, balance and coordination); Sensory (visual, auditory and speech abilities)
Skills	7 Ordinal variables	Basic (content and process skills); Cross-functional (social, complex problem-solving, technical, system and resource management skills)
Tasks	7 Ordinal variables	Non-routine cognitive analytic, non-routine cognitive interpersonal, routine cognitive, routine manual, non-routine manual physical adaptability, non-routine manual interpersonal adaptability
Stage 3: Influence of academic background on holding a job in each technological group		
Academic background variables		
Field of Studies	10 Binary variables	Education; Arts, Humanities & Languages; Social Sciences, Journalism & Information; Business, Administration & Law; Natural Sciences, Maths, Physics, Chemistry; ICT; Engineering, Manufacturing & Construction; Agriculture Forestry, Fishery & Veterinary; Health & Welfare; Services
Studies abroad as an undergraduate	1 Binary variable	No; Yes
Internship programmes as an undergraduate	1 Binary variable	No; Yes
Other languages	1 Binary variable	No; Yes
ICT level	3 Binary variables	None, Basic, Advanced
More formal education	8 Binary variables	No more; VET; Graduate; Postgraduate; VET + Graduate; VET + Postgraduate; Graduate + Postgraduate; VET + Graduate + Postgraduate
Educational mismatch	3 Binary variables	Over-educated; Well-educated; Under-educated
Control variables		
Gender	1 Binary variable	Male; Female
Age	3 Binary variables	Under 30 years old; 30–34 years old; over 35 years old

Table 2 (continued)

Variables	Type of variable	Categories
Nationality	1 Binary variable	Spanish; Other
Disability	1 Binary variable	No; Yes
Socioeconomic grant as an undergraduate	1 Binary variable	No; Yes
Type of university	1 Binary variable	Public; Private
Excellence grant as an undergraduate	1 Binary variable	No; Yes
Mobility for employment reasons	1 Binary variable	No; Yes
Work experience before graduation	1 Binary variable	No; Yes
Region of residence	20 Binary variables	19 regions of Spain and abroad
Number of employers	Numeric	

languages, and for *ICT skills* we consider three levels of computer skills (none, basic, and advanced). In a fully digitalized world, students who possess skills that enable them to use new technologies –many of which are related to ICT and include familiarity with commonly used programs—should be less vulnerable to the impact of digitalization (Cesco et al., 2021).

Another aspect considered is whether the graduate has undertaken *further formal education* in the form of VET and/or other graduate or postgraduate degrees (Cesco et al., 2021). In this regard, individuals are selected according to a particular degree, although the questionnaire asks whether the individual has completed more formal education before, during, or after the studies for which they were selected, which could be at a higher level (such as a master's degree or a doctorate) or at the same or lower level (such as another degree or vocational training cycles) and related to the same area or not. Up to a maximum of three can be reported. In this work, we consider several situations that result from combining different types of the Spanish education system that include both more vocational training and postgraduate studies (master's degree or PhD).

Finally, the role played by *educational mismatch in the job* is analysed. In general, graduates acquire both types of skills: general skills and more occupation-specific skills. When individuals are overeducated, the more specific human capital cannot easily be transferred to other sectors, and graduates in these fields are less likely to search for a job in other sectors (Lauder & Mayhew, 2020; Salas-Velasco, 2021). Moreover, they suffer skill depreciation when those skills attributed to their degrees are not put into practice. The survey allows us to obtain a subjective measure of vertical mismatch in the current job through the response to the question: In your opinion, what is the most appropriate level of education for this job? We identify vertical mismatch when graduates report that the most appropriate level of education is below their maximum level of education, taking into account not only the degree for which they have been selected for the survey, but also information on other studies they may have reported, such as a master's degree or a doctoral degree.

In order to control for individual heterogeneity among graduates, several control variables are also included in the multinomial model such as gender, age when the survey was completed, nationality, disability, type of university (private or public), socioeconomic grants as an undergraduate, excellence grants as an undergraduate, work experience before graduation, regional mobility due to employment reasons, number of employers since graduation, and region of residence. The categories of these variables are included in Table 2.

Unfortunately, the survey does not include information about the abilities, skills and task content of the job at the moment of the interview, or any measures of the impact of digitalization. To circumvent this shortcoming, we use the Occupational Information Network (O*NET) database (November-2019) compiled by the US Department of Labor as a source of information on the main characteristics of occupations and we merge it with individual EILU-2019 data based on current job occupation at the time of the interview.[4] Although the O*NET database is geared towards the occupational content of jobs in the American labour market, it has regularly been used to analyse countries other than the US, and the assumption that skill and content measures from one country can be generalized to other countries has been tested and largely holds (Cedefop, 2015; Handel, 2012). In this sense, we do not assume the equivalence of jobs in Spain and the US per se, but rather use

[4] To merge both databases, we mapped O*NET items to the corresponding occupations in SOC and then, using official ILO crosswalk, translated all SOC-based occupations into ISCO and then into CNO11, using official INE crosswalk.

Table 3 Descriptive statistics of digitalization measures for occupation at the time of interview

	Risk of automation	Advances in AI
Mean	0.282	3617
Median	0.129	3513
Standard deviation	0.290	0.512
Minimum	0.021	1849
Maximum	0.932	4355
Sample size/Population	26,994/196073	26,994/196073

Descriptive statistics are calculated using weights

Source own elaboration based on EILU-2019; Frey and Osborne (2017); Felten et al. (2018)

US data as an approximation of the general skills and task intensity distribution across occupations. Specifically, we use O*NET variables corresponding to the *skills and abilities required* from workers participating in each occupation and the *task content of jobs* (see Table 2). Respondents in O*NET indicate the importance of a given skill, ability, or task for their job on a scale from 1, not important, to 5, extremely important.

In order to map the occupation in which the graduate works four years after graduation in terms of the impact of digitalization, we also merge with EILU-2019 data of two measures of occupational susceptibility to digitalization that we interpret—following Fossen and Sorgner (2019)—as destructive and transformative impacts. To measure *destructive digitalization*, we use *automation risks* of occupations estimated by Frey and Osborne (2017) and later adapted to the Spanish classification of occupations by Fernández Alvaro (2018). The measure captures the risk of human workers being replaced by machines in the next 10–20 years based on expert judgments and selected characteristics of occupations from the O*NET database. We also use as an indicator of *transformative digitalization* a measure of past *advances in AI* developed by Felten et al. (2018). This measure does not rely on experts' predictions of the future. Instead, Felten et al. (2019) estimate progress slopes for nine categories of AI based on past developments in these technologies (in 2010–15) as reported by the AI Progress Measurement dataset provided by the Electronic Frontier Foundation and then connect advances in the AI categories to 52 abilities used by the O*NET database to describe job requirements. This allows them to measure progress in AI at the level of occupations. Large values of this measure indicate more pronounced developments in AI in a particular occupation, which is interpreted as a stronger transformative impact of digitalization upon that occupation, since human workers will work closely with AI technologies in transformed occupations consisting, at least partially, of new tasks or more complex versions of existing tasks, in which human labour has a comparative advantage. In this regard, rather than completely replacing human workers, AI is more likely to transform occupations.

Results

Some Descriptive Statistics of Digitalization

The combination of the two measures (risk of automation and advances in AI) will provide us with a characterization of which jobs recent Spanish graduates occupy when

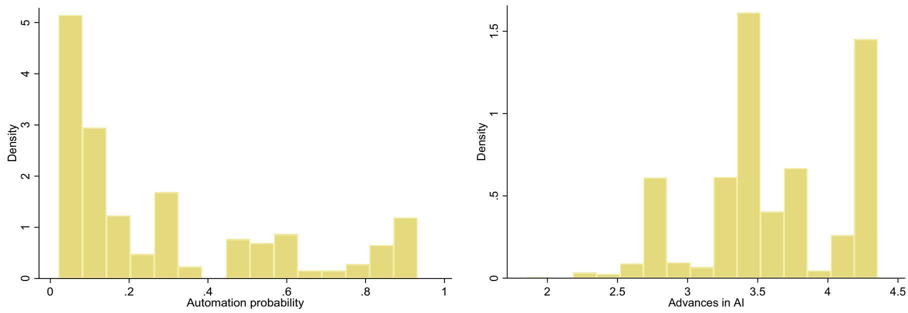

Fig. 1 Distribution of destructive and transformative digitalization measures for recent graduates in Spain (bin = 15). Values in the figures are weighted by the employment in each occupation. *Source* own elaboration based on EILU-2019; Frey and Osborne (2017); Felten et al. (2018)

entering the labour market. First, in Table 3, we present descriptive statistics for the risk of automation and advances in AI. It is worth noting that, on average, the risk of automation in the occupations held by recent Spanish graduates (0.282) is substantively lower than estimated by Fossen and Sorgner (2019) for the whole US population (0.579). As expected, the risk of automation is lower in jobs held by graduates that involve high educational requirements to perform mostly non-routine tasks in an unstructured environment (Arntz et al., 2016). In their widely cited paper, Frey and Osborne () distinguish between occupations with low risk (below 30%), medium risk (30–70%), and high risk (over 70%) of automation. If we compare our percentage of graduates in occupations within each group of automation risk with previous results, there are major differences. For example, only about 15% of recent graduates currently hold jobs with a high probability of being replaced by machines over the next 10–20 years, in contrast to 47% in the US or 36% in Spain. As regards the measure related to advances in AI, differences are not as large. We obtain an average of 3.617, whereas in the work by Fossen and Sorgner (2019) the mean is 3.170. This indicates that occupations held by recent graduates have made more progress in AI, which could be interpreted as a stronger transformative impact of digitalization on those occupations. Finally, we notice that the correlation between these two measures is large and negative (− 0.6928), thereby confirming that they are assessing different aspects of digitalization.

In order to gain a better picture of which kind of job the labour market is offering graduates, we use the graphical representation of both variables. Distribution for the risk of automation in Fig. 1 shows a U-shape, but is less pronounced than the usual bipolar structure of previous studies that focus on the whole population (Domenech et al., 2018; Frey & Osborne, 2017). This suggests that –among graduates– a smaller share of individuals face a very high risk (less than 15% of recent graduates) and that at the same time a large share face a very low risk of automation (more than 70%). Moreover, the middle of the distribution tends to have a greater mass; only a few jobs have medium automatability. The histogram corresponding to the measure of advances in AI displays a more similar pattern to a bell-shaped distribution, but with values skewed to the right (Felten et al., 2018). This means that a significant share of all individuals face moderate levels of transformation due to digitalization. Nonetheless, among graduates there are several individuals (occupations) with a transformative digitalization score of over four, indicating a very strong risk of transformation due to digitalization.

		Destructive Impact	
		Low	High
Transformative Impact	High	Rising Stars 32.4%	Machine Terrain 14.9%
	Low	Human Terrain 19.2%	Collapsing group 33.5%

Fig. 2 Distribution of recent graduates by technological occupation groups defined according to the transformative and destructive effects of digitalization. Values in the figure are weighted by the employment in each occupation. *Source* own elaboration based on EILU-2019

Mapping the Effects of Digitalization on Occupation

In this section, we map the occupations held by graduates four years after graduation in terms of the expected impact the new wave of digitalization will have upon them. We also describe the four major groups of occupations with regard to required abilities as well as skills and tasks performed.

Division into four groups is obtained by considering the median values of the two measures, weighted by Spanish graduate employment in the occupations (Fig. 2). Firstly, there are occupations with low destructive digitalization effects and, at the same time, low transformative effects. The tasks in these occupations cannot currently be performed by machines (Human Terrain). The second group consists of occupations with a high impact of transformative digitalization and a low risk of destructive digitalization (Rising Stars). These occupations face significant changes affecting skill requirements. Graduates working in these occupations will need a high level of flexibility to be able to adjust to rapid changes in their occupations and it is also important for them to keep up to date so that they are not displaced by other workers. The next group contains occupations with high destructive and low transformative effects. For these occupations, automation is total and these jobs will disappear for human workers (Collapsing Group). Finally, the last group is characterized by a high transformative and destructive impact of digitalization. Transformations in the work content of these occupations make human workers obsolete, such that they are no longer needed (Machine Terrain).

In terms of employment, most recent graduates hold occupations that fall into the collapsing or Rising Stars groups. They thus face either high levels of transformative digitalization or are more affected by destructive digitalization-but not both. 33.5% of all graduates are employed in occupations belonging to the collapsing group and 32.4% to the Rising Stars group, whereas less than one-fifth are employed in Human Terrain occupations and 14.9% in Machine Terrain occupations.

It should be noted that Fossen and Sorgner (2019) obtained the same ranking of groups but with more extreme accentuated proportions, showing that the impact of digitalization on the labour market of recent graduates differs from that of the population as a whole. In our case, there are more graduates in occupations not affected by digitalization in any significant way (Human Terrain). However, we also found more individuals in occupations that will be strongly affected by both digitalization types (Machine Terrain).

The use of knowledge, competencies and skills differs depending on the occupations performed and, more specifically, according to the tasks associated with the jobs held. In

Table 4 Characterization of technological occupational groups in terms of abilities, skills, and tasks (mean values)

	Human terrain (mean AI=3.43; mean risk aut.=0.06)	Rising stars (mean AI=4.18; mean risk aut.=0.08)	Collapsing (mean AI=3.10; mean risk aut.=0.58)	Machine terrain (mean AI=3.82; mean risk aut.=0.36)
Abilities (15)				
Cognitive	**0.192**	**0.975**	− 1059	**0.137**
Verbal abilities	**0.590**	**0.654**	− 0.683	− 0.465
Reasoning abilities	**0.117**	**0.983**	− 0.998	**0.082**
Quantitative abilities	− 0.293	**0.697**	− 0.422	− 0.098
Memory	**1223**	**0.286**	− 0.888	− 0.088
Perceptual abilities	− 0.315	**0.838**	− 0.965	**0.747**
Spatial abilities	− 0.489	**0.420**	− 0.464	**0.694**
Attentiveness	**0.487**	**0.577**	− 0.906	**0.227**
Psychomotor	− 0.622	**0.056**	− 0.031	**0.638**
Fine manipulative abilities	− 0.701	**0.156**	− 0.004	**0.491**
Control movement abilities	− 0.640	**0.113**	− 0.101	**0.693**
Reaction time and speed	− 0.433	− 0.144	**0.045**	**0.639**
Physical	**0.177**	− 0.345	**0.111**	**0.206**
Physical strength abilities	**0.210**	− 0.367	**0.108**	**0.214**
Endurance	**0.296**	− 0.295	**0.016**	**0.176**
Flexibility, balance, and coordination	**0.108**	− 0.330	**0.137**	**0.203**
Sensory	− 0.152	**0.356**	− 0.558	**0.629**
Visual abilities	− 0.520	**0.308**	− 0.395	**0.793**
Auditory and speech abilities	**0.600**	**0.328**	− 0.682	**0.107**
Skills (7)				
Basic	**0.671**	**0.789**	− 0.955	− 0.258
Content skills	**0.342**	**0.873**	− 0.815	− 0.326
Process skills	**1046**	**0.605**	− 1052	− 0.143

Table 4 (continued)

	Human terrain (mean AI=3.43; mean risk aut.=0.06)	Rising stars (mean AI=4.18; mean risk aut.=0.08)	Collapsing (mean AI=3.10; mean risk aut.=0.58)	Machine terrain (mean AI=3.82; mean risk aut.=0.36)
Cross-functional	− 0.094	**0.792**	− 0.988	**0.635**
Social skills	**0.960**	**0.392**	− 0.554	− 0.652
Complex problem-solving skills	**0.018**	**0.980**	− 0.992	**0.184**
Technical skills	− 0.650	**0.282**	− 0.525	**1,240**
System skills	**0.134**	**0.876**	− 0.984	**0.227**
Resource management skills	− 0.106	**0.749**	− 0.510	− 0.219
Tasks (7)				
Non-routine cognitive analytic	**0.189**	**0.807**	− 0.899	**0.125**
Non-routine cognitive interpersonal	**1064**	**0.372**	− 0.578	− 0.681
Routine cognitive	− 1225	− 0.236	**0.720**	**0.332**
Routine manual	− 0.814	− 0.248	**0.390**	**0.560**
Non-routine manual phys. adaptability	− 0.699	− 0.082	**0.125**	**0.659**
Non-routine manual interpersonal adaptability	**0.951**	**0.305**	− 0.495	− 0.603

Values in the table are weighted by the employment in each occupation

Bold values indicate above-average total level

Source own elaboration based on EILU-2019 and O*NET (November 2019) the next step, we analyse the characteristics of the occupations in the four groups derived from the digitalization analysis in order to ascertain which are more prevalent. Specifically, we examine several dimensions related to worker requirement and occupational requirement: abilities, skills, and tasks. As already mentioned, we assigned the O*NET skills, abilities, and tasks items to the EILU data and aggregated them, as shown in Table 4.[5] Values marked in bold represent an above-average level compared to the total sample. Individuals in the Rising Stars group require above-average levels in all cognitive abilities –both basic and especially cross-functional skills such as complex problem solving– and tasks are basically non-routine cognitive. Occupations need human input and can only be performed by workers with high analytical capacity and adaptability. In contrast, individuals in the Collapsing group are characterized by the use of physical abilities and the performance of routine tasks that follow well-defined rules that are susceptible to codification and to being performed by a machine. The abilities required in occupations belonging to the Machine Terrain group are mainly psychomotor-such as reaction time and speed, fine manipulative and control movement and also sensory—such as visual abilities. In this group, technical skills stand out, and the tasks performed are manual—both routine and non-routine (physical adaptability). As expected, the terrain group demand sensory abilities such as auditory and speech abilities, and certain cognitive abilities such as memory and verbal abilities along with basic skills, and the type of tasks performed in this group are non-routine, being both cognitive and manual with an interpersonal component.

The Influence of Academic Background

Finally, we analyse the influence of individuals' academic background on the probability of belonging to each technological occupational group by estimating a multinomial logit model in which the dependent variable Y identifies the technological group and takes the value 1–4. As explanatory variables and as mentioned earlier—we include the graduate's academic background, measured by several indicators. First, we considered the field of education of the degree by which the individual is selected in the EILU survey, the level of knowledge of information and communication technologies (ICT) and of other languages, together with having undertaken further formal education in the form of VET and/or other graduate or postgraduate degrees. Second, we accounted for international experience during the degree and also included the specific human capital stem from internships. Finally, we examined educational mismatch in the current employment. In order to control for individual heterogeneity among graduates, the control variables reported in Table 2 are also included in the model The descriptive statistics of the variables are reported in Table 5. The estimation results appear in Table 6 and show that all variables are significant. It should be pointed out that in order to estimate the model, one category of the dependent variable must be set as the reference category. In our case, this is the Collapsing group. In this type of model, the probability of being in any of the other categories is compared to the probability of being in the reference

[5] We first standardized the values of each item. Using these standardized items, we then created the composite measures as a sum of constituent items, which in the next step are again standardized to have a mean 0 and standard deviation 1. This allows us to interpret a unit change in the mean values of each composite measure as a one standard deviation. Standardization is also required because each composite measure uses various numbers of items that also have different ranges (Acemoglu & Autor, 2011). In all the process, we weighted by graduate employment in each occupation.

Table 5 Descriptive statistic of control and academic background variables

	Freq.	Percent
Control variables		
Gender		
Men	82757	42.21
Female	113316	57.79
Age		
Under 30 years old	96587	49.26
30-34 years old	56952	29.05
Over 35 years old	42534	21.69
Nationality		
Spanish	191332	97.58
Other	4741	2.42
Disability		
No	194326	99.11
Yes	1747	0.89
Socioeconomic grant as an undegraduate		
No	126373	64.45
Yes	697	35.55
Type of university		
Public	162891	83.08
Private	33182	16.92
Excellence grant as an udergraduate		
No	182183	92.92
Yes	1389	7.08
Mobility for employment reasons		
No	161854	82.55
Yes	34219	17.45
Working experience before graduation		
No	103871	52.98
Yes	92202	47.02
Region of residence		
Andalucía	22732	11.59
Aragón	5648	2.88
Asturias	3339	1.70
Baleares	3878	1.98
Canarias	5852	2.98
Cantabria	1918	0.98
Castilla y León	10089	5.15
Castilla - La Mancha	703	3.59
Cataluña	29988	15.29
Comunitat Valenciana	18783	9.58
Extremadura	3245	1.65
Galicia	789	4.02
Madrid	42012	21.43
Murcia	5717	2.92
Navarra	2593	1.32
País Vasco	9544	4.87
Rioja	1133	0.58
Ceuta	162	0.08

Table 5 (continued)

	Freq.	Percent
Melilla	282	0.14
Abroad	14238	7.26
Number of employers	196073	3.14/2.20[a]
Academic background		
Field of Studies		
Education	7176	3.66
Arts, Humanities & Languages	40453	20.63
Social Sciencies, Journalism & Information	1758	8.97
Business, Administration & Law	39788	20.29
Natural Sciecnes, Maths, Physics & Chemistry	9972	5.09
ICTs	6535	3.33
Engineering, Manufacturing & Construction	34836	17.77
Agriculture, Forestry, Fishery & Veterinary	3522	1.80
Health & Welfare	29795	15.20
Services	6416	3.27
Studies abroad as an undergraduate		
No	161605	82.42
Yes	34468	17.58
Intership programmes as an undergradute		
No	50014	25.51
Yes	146059	74.49
Other languages		
No	8419	4.29
Yes	187654	95.71
ICTs level		
None	2275	11.60
Basic	131912	67.28
Advanced	41411	21.12
More formal education		
No more	59068	30.13
VET	16553	8.44
Gradute	26523	13.53
Postgraduate	63954	32.62
VET+Graduate	3828	1.95
VET+Postgraduate	7456	3.80
Graduate+Postgraduate	16502	8.42
VET+Graduate+Postgraduate	2189	1.12
Educational mismatch		
Over-educated	82900	42.28
Well-educated	103309	52.69
Infra-educated	9864	5.03

Values in the table are weighted by the employment in each occupation

Source own elaboration based on EILU-2019

[a]Mean/standard deviation

category. These relative probabilities are the predicted log odds (the logarithmic of the

Table 6 Multinomial Logit for the probability of belonging to each technological occupational group

	All graduates		
	Humman terrain	Rising stars	Machine terrain
	Coef.	Coef.	Coef.
Academic background			
Field of studies (ref: education)			
Arts, Humanities & Languages	0.447***	− 0.103*	− 1.301***
Social Sciencies, Journalism & Information	− 2.600***	− 0.209***	− 0.494***
Business, Administration & Law	− 3.366***	0.194***	− 1.923***
Natural Sciecnes, Maths, Physics & Chemistry	− 0.605***	1.312***	0.242***
ICTs	− 0.922***	1.336***	1.575***
Engineering, Manufacturing & Construction	− 1.438***	2.234***	0.216***
Agriculture, Forestry, Fishery & Veterinary	− 1.497***	2.228***	0.325***
Health & Welfare	− 1.528***	3.605***	0.287***
Services	− 1.731***	− 0.502***	− 1.397***
Studies abroad as an undergraduate (ref: No)			
Yes	− 0.356***	− 0.018	− 0.132***
Intership programmes as an undergradute (ref: No)			
Yes	0.212***	0.086***	0.073***
Other languages (ref: No)			
Yes	0.299***	0.091**	− 0.064*
ICTs level (ref: none)			
Basic	− 0.482***	− 0.324***	− 0.267***
Advanced	− 0.675***	− 0.326***	0.117***
More formal education (ref: No)			
VET	0.222***	− 0.016	0.257***
Gradute	1.015***	0.340***	0.165***
Postgraduate	1.695***	1.173***	0.703***
VET+Graduate	0.856***	0.071	− 0.212**
VET+Postgraduate	1.919***	1.267***	0.949***
Graduate+Postgraduate	2.565***	1.390***	0.604***
VET+Graduate+Postgraduate	2.714***	1.326***	0.737***
Educational missmatch (ref: Over-educated)			
Well-educated	2.049***	1.436***	0.765***
Infra-educated	2.514***	2.023***	0.906***
Constant	− 1.754***	− 1.956***	− 0.683***
N	196073		
LogL	− 181578.9		
Chi2/p-value	100936.5/0.00		
AIC	363481.9		
BIC	365132.1		

Control variables included: gender, age, nationality, disability, type of university, socioeconomic grants as an undergraduate, excellence grants as an undergraduate, mobility for employment reasons, work experience before graduation, number of employers since graduation, region of residence

Source own elaboration based on EILU-2019

***, **, *Significant at 1%, 5%,10%, respectively. Robust standard error

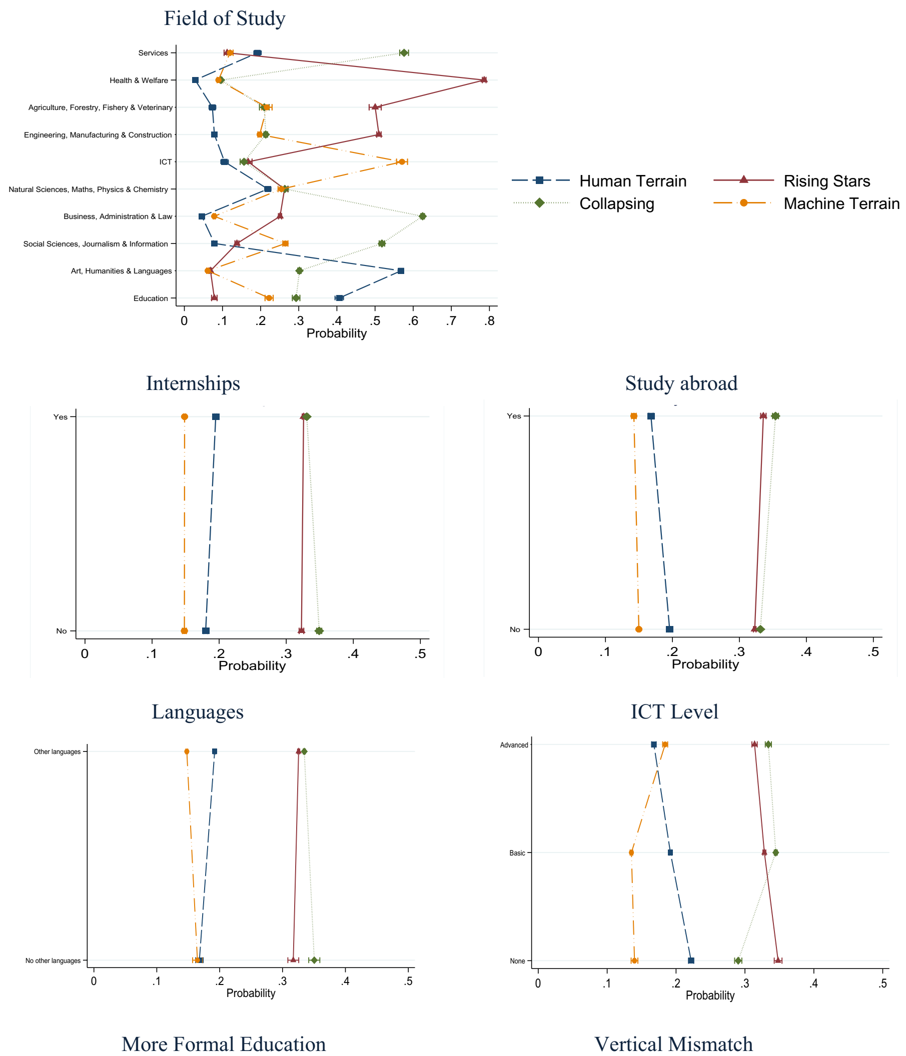

Fig. 3 Predicted margins for academic background factors for each technological occupational group with 95% confidence intervals

probabilities). More specifically, the estimated coefficients show how the log-odds of being in a particular category change when a binary variable changes from 0 to 1 compared to the reference category. If the coefficient is positive (negative), it means that changing the binary variable from 0 to 1 increases (decreases) the log-odds of being in this particular technological group compared to the reference group. The coefficient 0.212 for the *internship programmes as an undergraduate* variable in the Human Terrain group means that when graduates take part in internship programmes, the log-odds of being in the Human Terrain group compared to the Collapsing group (reference category) increases by 0.212. The coefficients for the other two technological groups are also positive (0.086 and 0.073), meaning that participation in internships increases the log-odds of being in each technological group in comparison to the Collapsing group.

Since the coefficients from the multinomial logit can prove difficult to interpret because they are relative to the reference category, we use another way to evaluate the effect of explanatory variables, which is to examine the marginal effect of changing their values on the probability of being in any specific category of the dependent variable. These marginal effects are plotted in Fig. 3.

As we progress up the educational ladder, education moves from being generalist to more specialized. University graduates have not only acquired a higher level of education but their learning is also focused on a particular area of knowledge. Looking at the marginal effects of field of education in Fig. 3, we see that having completed a degree in fields such as Health and Welfare, Agriculture, Forestry, Fihery and Veterinary, Science or Engineering, Manufacturing and Construction affords a greater probability of belonging to the Rising Stars group in which the destructive effects of automation are lower but in which the need to update skills is greater. On the other hand, graduates in Social Sciences, Journalism, and Information or Business, Administration and Law are more likely to belong to the Collapsing group, given that many occupations associated with these programmes –such as office administration, bookkeeping or financial service sales– face a high risk of automation. As expected, graduates in ICT are more likely to belong to the Machine Terrain group, and graduates in Education or Arts and Humanities have a greater chance of belonging to the Human Terrain group. One possible explanation for these results is the type of human capital that individuals acquired during higher education. Degrees in some fields provide more highly specialized skills that are largely occupation-specific and their transferability across jobs is limited (Salas-Velasco, 2021). Others produce graduates with highly adaptable and flexible skills that are clearly transferable to several jobs. Such is the case, for example, for STEM degrees that provide skills such as analytical thinking, quantitative reasoning or problem-solving.

Our results show that internships reduce the probability of belonging to the Collapsing group and slightly increase the probability of being in an occupation within the Rising Stars group (Fig. 3). Therefore, the work experience related to the degree and that is provided by internships reduces the risk of automation. Having studied abroad is seen to increase the probability of belonging to both groups.

Embedded learning activities were perceived as broadly useful to graduates' skill development, gaining relevant experience, provision of networking opportunities, and employment prospects-albeit in varying ways (Jackson & Bridgstock, 2021). Our results show that a knowledge of other languages slightly decreases the probability of belonging to the Collapsing group and increases the probability of being in an occupation in the rising group. However, ICT skills are not an incentive to take up a less vulnerable job. Such skills might already be taken for granted in the digital world in which we live and a basic knowledge thereof is assumed.

As regards having more formal education, it is difficult to gauge how the comprehensiveness of other studies affects the chances of belonging to a technological occupational group, since some studies complement others and provide graduates with the skills or experience they lack. Looking at Fig. 3, we discover two facts: the probability of belonging to the Collapsing group is always lower when an individual has more studies, regardless of the level or type of studies. Moreover, having other studies increases the probability of belonging to the Human Terrain group. In contrast, the probability of belonging to the Machine Terrain group hardly changes when graduates take other studies. Furthermore, the potential complementarity of studies reduces the possibility of being more exposed to automation.

In sum, most of the factors analysed increase the probability of belonging to the Rising Stars group or decrease the probability of belonging to the Collapsing group. In general, academic background improves the situation of graduates in that it allows them to work in occupations that are less exposed to automation. In line with the notion of a race between technology and education, it seems that technology is complementary to skilled labour.

As already mentioned in the literature, some graduates are unable to take advantage of their skills due to the low demand for these skills in the labour market, and accept jobs in which the required education does not correspond with their level of education. As they work in an occupation that is not well-matched, the risk of being displaced by machines could be higher. In short, educational mismatch (in particular, over-education) could have an effect on the risk of automation. As highlighted by the European Commission (2013), it should be considered that the incidence of mismatch is likely to increase in the future even more as a result of further automation processes and developments in new technologies. Two types of education-job mismatch are defined in the literature: vertical mismatch occurs when graduates work in non-graduate jobs, while so-called horizontal mismatch appears when there is no relation between workers' field of study and their occupation. In our case, we only consider vertical mismatch.[6] In general, graduates acquire both types of skills; general skills and more occupation-specific skills. When individuals are overeducated, the more specific human capital cannot easily be transferred to other sectors, and graduates in these fields are less likely to search for a job in other sectors (Salas-Velasco, 2021). Moreover, they suffer skill depreciation when those skills attributed to their degrees are not put into practice. When comparing predictive probabilities for individuals who are overeducated, the probability of belonging to the Collapsing group is just over twice the probability of belonging to the Rising Stars group. The difference in probabilities in the case of well-matched graduates is not as great and has the opposite sign, since it is higher in the rising group.

Discussion and Conclusions

The exact impact of new technologies on society is still unknown, although the fact that they will bring about profound and rapid change seems almost certain. New technologies are likely to reshape labour markets in the long run and to lead to a reallocation of the types of skills that the workers of tomorrow will need. To alleviate the risks of this reallocation, it is important for educational systems-and in particular for higher education institutions-to adapt rapidly to the demands of new jobs. Previous studies indicate that the relationship between automation and age is U-shaped, and the more pronounced effect of automation among younger workers could result in youth unemployment (Domenech et al., 2018; Nedelkoska & Quintini, 2018). On the other hand, further education enables the acquisition of skills in areas where human capabilities still outstrip those of machines. As young people with a higher educational level and with better skills, graduates are expected to be able to adapt more quickly to new job requirements, especially in those new positions and professions created around new technologies.

[6] Although the survey asks whether "*the current job is closely related, somewhat related or not related to the field of your degree*", we cannot build a measure of horizontal mismatch because interviewees could have more formal education in different fields of education, and their current job could be related to this other formal education.

This work seeks to identify those recent Spanish graduates who are likely to struggle in future labour markets and those who will be the winners in the digital era. A priori, our results show that the occupational structure of recent graduates puts them at a low risk of technology exposure since the share of those with a high risk of automation (15%) is lower than obtained by Domenech et al. (2018) for the population as a whole (36%) in Spain. A more detailed analysis, consisting of mapping occupations according to the classification of Fossen and Sorgner (2019), reveals that a substantial share of graduates face either high levels of transformative digitalization or are more affected by destructive digitalization –but not both. For graduates in the former group, skills correlate with flexible task performance and the ability to work in a complementary way with technology. They are less likely to be displaced by automation but are subject to rapid changes in their jobs that require them to update their skills (*upskilling*). Graduates with high destructive digitalization effects are the most vulnerable and will have to reskill sooner or later (*re-skilling*). Finally, most of the different academic characteristics we evaluate are relevant for explaining vulnerability to digitalization. The choice of the field of study has important implications, and fields such as health and welfare, agriculture or engineering, manufacturing and construction are associated with less vulnerable occupations. Vulnerability may be conjectured to be lower for graduates in fields that provide more occupation-specific skills rather than more general skills. In addition, graduates who take jobs that require a lower level of education than higher education (over-educated graduates) are at greater risk of being displaced by machines. This is another consequence of educational mismatch, together with lower wages, more precarious careers or skill depreciation.

Overall, our results show that the remaining factors associated with academic background improve the position of graduates by allowing them to work in occupations that are less exposed to digitalization. Internship experience and a knowledge of other languages– can curb the risk of digitalization by reducing the probability of being in the most vulnerable group the Collapsing group– and by increasing the probability of being in the Rising Stars group. Having studied abroad increases the probability of being in both groups. The only factor that does not improve the chances of being in groups less exposed to digitalization is ICT skills. This suggests that in the digital world in which we live, such skills are already taken for granted, and basic knowledge is assumed.

Our results have some *practical implications* for higher education stakeholders. Firstly, they call for a reduction in the level of educational mismatch among university graduates. Since it may be difficult to influence the increase in demand for employment in certain occupations, this could be achieved by improving counselling activities for young people in their choice of study field. In addition, given the pace of technological change, anticipating training needs as well as skills and abilities requirements proves crucial. To this end, it is advisable to intensify and explore new forms of cooperation between firms and educational institutions so that there is constant feedback between the two. One example would be to introduce dual higher education programmes. Moreover, graduates and firms need to be made aware of the importance of lifelong learning. Intensifying training during adult life facilitates workers' gradual adaptation to technological changes and is key to individual upskilling and re-skilling. In this regard, universities should acknowledge the importance of these programmes and should extend the teaching offer in this direction. Finally, it is necessary to improve the efficiency of the education system so that it is able to provide the skills required by new technologies. In this context, we wish to highlight the importance of introducing more entrepreneurial skills into university programmes or flexibilising curricula to enable students to better adjust their education pathways to labour market needs. Digitalization has blurred the traditional boundaries between sciences, making cross-disciplinary knowledge necessary. In sum, if it is to succeed in the digital era, the education system should supply more flexible workers who are capable of reinventing themselves so as not to be excluded from the labour market. In addition, companies should interact with the education system and provide their workers with access to training activities, inside or outside the workplace. Nevertheless, more research is needed to determine the real effect of digitalization on employment and higher education, as the debate concerning the disruptive impact of technology on jobs remains open and has mainly focused on jobs that will be lost rather than on the types of jobs that will be created.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. No funding was received to assist with the preparation of this manuscript.

Data Availability The data that support the findings of this study are available from the corresponding author, upon request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Acemoglu, D. & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings, In Handbook of labor economics, 4:1043-1171, Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2018). The race between machine and man: Implications of technology for growth, factor shares and employment. *American Economic Review, 108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188–2244. https://doi.org/10.1086/705716

Akour, M., & Alenezi, M. (2022). Higher education future in the era of digital transformation. *Education Sciences, 12*(11), 784. https://doi.org/10.3390/educsci12110784

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis OECD social employment and migration working papers No. 189*. OECD Publishing.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters, 159*, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Autor, D., & Dorn, D. (2009). This job is "getting old": Measuring changes in job opportunities using occupational age structure. *American Economic Review, 99*(2), 45–51. https://doi.org/10.1257/aer.99.2.45

Autor, D., Levy, F., & Murname, R. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Belchior-Rocha, H., Casquilho-Martins, I., & Simões, E. (2022). Transversal competencies for employability: From higher education to the labour market. *Education Sciences, 12*(4), 255. https://doi.org/10.3390/educsci12040255

Bellas, M. L. (2001). Investment in higher education: Do labor market opportunities differ by age of recent college graduates? *Research in Higher Education*, *42*(1), 1–25. https://doi.org/10.1023/A:1018786610185

Bolli, T., Caves, K., & Oswald-Egg, M. E. (2021). Valuable experience: How university internships affect graduates' income. *Research in Higher Education*, *62*(8), 1198–1247. https://doi.org/10.1007/s11162-021-09637-9

Bonfield, C. A., Salter, M., Longmuir, A., Benson, M., & Adachi, C. (2020). Transformation or evolution?: Education 4.0, teaching and learning in the digital age. *Higher Education Pedagogies, 5*(1), 223–246. https://doi.org/10.1080/23752696.2020.1816847

Bosio, G., & Cristini, A. (2018). Is the nature of jobs changing? The role of technological progress and structural change in the labour market. In G. Bosio, T. Minola, F. Origo, & S. Tomelleri (Eds.), *Rethinking entrepreneurial human capital. Studies on entrepreneurship, structural change and industrial dynamics.* Springer. https://doi.org/10.1007/978-3-319-90548-8_2

Bowles, J. (2014). The computerisation of European jobs. Bruegel blog

Brunello, G., & Wruuck, P. (2019). Skill Shortages and skill mismatch in Europe: A review of the literature. *IZA Institute of Labor Economics*. https://doi.org/10.2139/ssrn.3390340

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings, 108*, 43–47. https://doi.org/10.1257/pandp.20181019

Cedefop. (2015). *Skills, qualifications and jobs in the EU: The making of a perfect match? Evidence from cedefop's European skills and jobs survey*. Publications Office. https://doi.org/10.2801/606129

Cesco, S., Zara, V., De Toni, A. F., Lugli, P., Evans, A., & Orzes, G. (2021). The future challenges of scientific and technical higher education. *Tuning Journal for Higher Education, 8*(2), 85–117. https://doi.org/10.18543/tjhe-8(2)-2021pp85-117

Croce, G., & Ghignoni, E. (2024). The multifaceted impact of erasmus programme on the school-to-work transition: A matching sensitivity analysis. *Research in Higher Education*. https://doi.org/10.1007/s11162-024-09774-x

Di Meglio, G., Barge-Gil, A., Camiña, E., & Moreno, L. (2022). Knocking on employment's door: Internships and job attainment. *Higher Education, 83*, 137–161. https://doi.org/10.1007/s10734-020-00643-x

Domenech, R., García, J. R., Montañez, M., & Neut, A. (2018). Afectados por la revolución digital: El caso de España. *Papeles De Economía Española, 156*, 128–145.

Eurofound. (2008). Recent changes in the jobs structure of the EU. Technical Report. Dublin: Eurofound.

European Commission. (2013). *Employment and social developments in Europe 2012*. Luxembourg: Office for Official Publications of the European Communities.

Felten, E. W., Raj, M., & Seamans, R. (2018). A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and Proceedings, 108*, 54–57. https://doi.org/10.1257/pandp.20181021

Felten, E. W., Raj, M., & Seamans, R. (2019). The occupational impact of artificial intelligence: Labor, skills, and polarization. *NYU Stern School of Business*. https://doi.org/10.2139/ssrn.3368605

Fernández Álvaro, C. (2018). Automatización del empleo. Adaptación de las probabilidades de Frey y Osborne para el cálculo. XX Jornadas de Estadística de las Comunidades Autónomas.

Fernández-Macías, E. (2012). Job polarisation in Europe? Changes in the employment structure and job quality, 1995–2007. *Work and Occupations, 39*(2), 157–182. https://doi.org/10.1177/07308884114

Fossen, F., & Sorgner, A. (2019). Mapping the future of occupations: Transformative and destructive effects of new digital technologies on jobs. *Foresight and STI Governance, 13*(2), 10–18. https://doi.org/10.17323/2500-2597.2019.2.10.18

Fossen, F., & Sorgner, A. (2022). New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data. *Technological Forecasting and Social Change, 175*, 121381. https://doi.org/10.1016/j.techfore.2021.121381

Frey, C. B., & Osborne, M. A. (2013). *The future of employment: How susceptible are jobs to computerization?* Oxford University Paper.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techfore.2016.08.019

García-Aracil, A. (2008). College major and the gender earnings gap: A multi-country examination of postgraduate labour market outcomes. *Research in Higher Education, 49*, 733–757. https://doi.org/10.1007/s11162-008-9102-y

Georgieff, A., & Hyee, R. (2021). *Artificial intelligence and employment new cross-country evidence, OECD social employment and migration working papers No. 265*. OECD Publishing.

Gonzalez Vazquez, I., Milasi, S., Carretero Gomez, S., Napierala, J., Robledo Bottcher, N., Jonkers, K., Goenaga, X. (eds.), The changing nature of work and skills in the digital age, EUR 29823 EN, Publications Office of the European Union, Luxembourg, 2019.

González-Vázquez, I., Milasi, S., Carretero-Gomez, S., Napierala, J., Robledo Bottcher, N., Jonkers, K., et al. (2019a). The changing nature of work and skills in the digital age. *EU Science Hub*. https://doi.org/10.2760/679150

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review, 104*(8), 2509–2526.

Gouda, H. (2022). Exploring the effects of learning abilities, technology and market changes on the need for future skills. *Higher Education, Skills and Work-Based Learning*. https://doi.org/10.1108/heswbl-10-2021-0200

Handel, M. (2012). *Trends in job skill demands in OECD countries OECD social, employment and migration working papers, No. 143*. OECD Publishing.

Hernández Lahiguera, L., Pérez García, F., & Serrano Martínez, L. (2020). Capital humano, digitalización y crecimiento económico. *Papeles De Economía Española, 166*, 18–32.

INE. (2020). *Encuesta de Inserción Laboral de Titulados Universitarios 2019*. Metodología. Instituto Nacional de Estadística.

Jackson, D., & Bridgstock, R. (2021). What actually works to enhance graduate employability? The relative value of curricular, co-curricular, and extra-curricular learning and paid work. *Higher Education, 81*(4), 723–739. https://doi.org/10.1007/s10734-020-00570-x

Jung, J. (2022). Working to learn and learning to work: Research on higher education and the world of work. *Higher Education Research & Development, 41*(1), 92–106. https://doi.org/10.1080/07294360.2021.2002274

Kornelakis, A., & Petrakaki, D. (2020). Embedding employability skills in UK higher education: Between digitalization and marketization. *Industry and Higher Education, 34*(5), 290–297. https://doi.org/10.1177/0950422220902978

Lauder, H., & Mayhew, K. (2020). Higher education and the labour market: An introduction. *Oxford Review of Education, 46*(1), 1–9. https://doi.org/10.1080/03054985.2019.1699714

Lawrence, M., Roberts, C. & King, L. (2017). Managing automation: Employment, inequality and ethics in the digital age. IPPR Commission on economic justice discussion paper.

Lincoln, D., & Kearney, M. L. (2019). Promoting critical thinking in higher education. *Studies in Higher Education, 44*(5), 799–800. https://doi.org/10.1080/03075079.2019.1586322

Lladós-Masllorens J. (2019). Surfing the waves of digital automation in Spanish labor market. In: Visvizi A., Lytras M. (eds) *Research & Innovation Forum 2019. RIIFORUM 2019. Springer Proceedings in Complexity*. Springer. https://doi.org/10.1007/978-3-030-30809-4_41

McGuinness, S., Pouliakas, K., & Redmond, P. (2021). Skills-displacing technological change and its impact on jobs: Challenging technological alarmism? *Economics of Innovation and New Technology*. https://doi.org/10.1080/10438599.2021.1919517

Monteiro, S., Almeida, L., & García-Aracil, A. (2021). It's a very different world: Work transition and employability of higher education graduates. *Higher Education, Skills and Work-Based Learning, 11*(1), 164–181. https://doi.org/10.1108/HESWBL-10-2019-0141

Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training OECD social, employment and migration working papers No. 202*. OECD Social: OECD Publishing, Paris. https://doi.org/10.1787/2e2f4eea-en

OECD Regional Outlook. (2019). *Leveraging megatrends for cities and rural areas*. OECD Publishing.

Oesch, D., & Rodriguez Menes, J. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990–2008. *Socio-Economic Review, 9*(3), 503–531. https://doi.org/10.1093/ser/mwq029

Osmani, M., Weerakkody, V., Hindi, N. M., et al. (2015). Identifying the trends and impact of graduate attributes on employability: A literature review. *Tertiary Education Management, 21*, 367–379. https://doi.org/10.1080/13583883.2015.1114139

Pajarinen, M. & Rouvinen, P. (2014). Computerization threatens one third of Finish employment, ETLA Brief No. 22.

Pouliakas, K. (2018). Determinants of automation risk in the EU labour market: A skills-needs approach. IZA Discussion Paper No. 11829.

Randstad (2021) Flexibility@Work2021: Embracing change. Randstad

Salas-Velasco, M. (2021). Mapping the (mis)match of university degrees in the graduate labor market. *Journal for Labour Market Research, 55*, 14. https://doi.org/10.1186/s12651-021-00297-x

Scandurra, R., Kelly, D., Fusaro, S., Cefalo, R., & Hermannsson, K. (2023). Do employability programmes in higher education improve skills and labour market outcomes? A systematic review of academic literature. *Studies in Higher Education*. https://doi.org/10.1080/03075079.2023.2265425

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics, 24*(2), 235–270. https://doi.org/10.1086/499972

Suleman, F. (2018). The employability skills of higher education graduates: insights into conceptual frameworks and methodological options. *Higher Education, 76*(2), 263–278.

Teichler, U. (2009). *Higher education and the world of work. Conceptual frameworks, comparative perspectives, empirical findings*. The Netherlands: Sense Publishers.

Tomaszewski, W., Perales, F., Xiang, N., & Kubler, M. (2021). Beyond graduation: Socio-economic background and post-university outcomes of Australian graduates. *Research in Higher Education, 62*, 26–44. https://doi.org/10.1007/s11162-019-09578-4

Wright, R., Ellis, M., & Townley, M. (2017). The matching of STEM degree holders with STEM occupations in large metropolitan labor markets in the United States. *Economic Geography, 93*(2), 185–201. https://doi.org/10.1080/00130095.2016.1220803

Xu, Y. J. (2013). Career outcomes of STEM and Non-STEM college graduates: Persistence in majored-field and influential factors in career choices. *Research in Higher Education, 54*(3), 349–382. https://doi.org/10.1007/s11162-012-9275-2