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Digital economy, technological competencies and the job matching process

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Abstract

Mastering digital skills is an increasingly important factor in the job matching process. This paper employs experimental methods to study how recruiters assess digital skills in the labour markets of Germany, Italy, and the United Kingdom. The aim is to determine the causal impact of job applicants' digital competences on recruiters' assessment within the hiring process. The analysis further explores the heterogeneous effects of digital skills in the distribution of opportunities for candidates with varying levels of education applying to high- and mid/low-skilled jobs. Our results show that intermediate and advanced digital skills increase a candidate's employability, with larger effects in the UK, a highly flexible labour market characterised by the relevance of general educational skills and relatively high returns to tertiary education. Focusing on heterogeneity by education and job types, the impact of digital skills is not univocal and highlights differing patterns across labour markets in shaping job candidate opportunities.

JEL Classification: H25, H71, L25, D22, D25, L20
Keywords: Digital skills, Education, Hiring intentions, Job matching, Factorial survey experiment, Germany, Italy, United Kingdom

1. Introduction

Over the last decade, the demand for digital skills in the labour market has been heavily shaped by economic, social, and industrial transformations. The world economy has witnessed significant improvements and advances in automation, digitalisation and, more recently, in the development of artificial intelligence. Digital skills are increasingly recognised as fundamental skills in the job matching process, as they enable workers to be more flexible in their approach to task-related issues and better adapt to shifts in demand for goods and services, thereby increasing their job mobility and employability (OECD, 2017).[1] At the same time, the broader application of digital technology encourages enterprises to pursue high-road market competition strategies, constantly strengthening digital innovation (Autor, 2015; Lordan and Neumark, 2018; Modestino et al., 2020). These changes have undoubtedly increased productivity worldwide and created new job opportunities across sectors and countries, driving the demand for digital skills (CEDEFOP, 2021). Side by notable layoffs among routine manual as well as non-manual, clerical, jobs (Autor, 2019; Autor et al., 2003; Goos et al., 2014), new job opportunities have been associated with an increase in the demand for highly digital skilled labour and highly educated workers (Bode & Gold, 2018; Falk & Biagi, 2017), with strong returns in terms of wages. The international literature, in fact, stresses the high correlation existing between education and skills, on the one hand, and skills and wages on the other (see OECD & Statistics Canada, 2000).

As the demand for technological competences raises, it becomes increasingly relevant to understand the role of digital skills in influencing employability and related labour market outcomes not only for highly educated job seekers, but also for individuals with mid-level educational attainments. Some contributions, in fact, highlight the complementarity between cognitive and noncognitive, manual, skills (Deming & Noray, 2018), while others (Autor, 2019) observe a significant deskilling in non-college labour markets, due to the impact of automation and globalization. Especially in the US labour market, in fact, middle-skill production and clerical

[1] In this article, we consider (digital) skills as an individual characteristic of applicants rather than a multi-dimensional feature of jobs, as elsewhere in the literature (Minardi et al., 2023). This means that we do not refer to an organisational understanding of skills (the sets of occupational and organizational skill requirements), but as characteristics of the individual (potential) workers, valued within the hiring process.

jobs have been the main targets of technological redundancies that have pushed non-college workers into lower-wage jobs requiring fewer specialised skills (Autor & Dorn, 2013).

Less is known about the interplay between digital skills and education in shaping job chances for candidates applying to high- versus mid-level jobs. If increasing digital skills can benefit less educated adults (Peng, 2017; Vaske, 2015) or can exert a positive impact on the academic achievement of students with low performance or working-class background (Pagani et al., 2016), then digital skills may have a compensatory effect in cases where workers lack adequate formal education or when they apply for higher-level occupations, increasing not only their employability but also their career opportunities.

In this article, we conduct a cross-national factorial survey experiment to measure recruiters' hiring intentions based on fictitious candidates' levels of digital skills. We do it for middle- and high-level job positions and combine them with different educational attainments to look for possible compensation effects. The analysis focuses on three European contexts, namely Germany, Italy, and the United Kingdom, which represent different education and labour market systems. Using an online survey, nearly 700 managers per country who are responsible for hiring decisions in their organisation were asked to rate hypothetical candidates with different levels of digital skills, education, and other socio-demographic characteristics applying for different jobs, thus simulating the hiring process. Several recent studies rely on experimental methods to better understand hiring intentions as they are ideal to identify the causal effects of candidate characteristics on employers' ratings (Damelang et al., 2019; Damelang & Abraham, 2016; Di Stasio, 2014a; Di Stasio & Van de Werfhorst, 2016; Protsch & Solga, 2017; Zamberlan et al., 2024).

Results show that having more advanced digital skills consistently increases employability across different job profiles, for both high- and middle-level jobs. Compared to basic digital skills, having intermediate skills increases the probability of being hired by 2.7 %, while having advanced skills increases the probability by 7.1%, indicating a positive, statistically significant, effect. Advanced digital skills increase employability more than tertiary education, with a higher magnitude in the UK, a flexible labour market characterised by the predominance of general skills. In Germany and Italy, formal educational attainment continues to have a strong impact on employability, overshadowing the impact of intermediate digital skills compared to basic skills.

The paper is organized as follows. Section 2 provides some background information about the interplay between digital skills and formal education on workers' employability, while Section 3 outlines the research questions. Section 4 describes the research design and the analytic strategy. Section 5 presents the results, and Section 6 concludes by providing a discussion of the results.

2. Digital skills and employability in different European contexts

Digitalisation processes are among the major structural changes that have radically changed OECD economies and labour markets in the last four decades. Digitalisation can be broadly defined as the "increasing use and networking of digital devices and the associated changes in products, services and processes" (Warning & Weber, 2018:5).[2] As such, digitalisation is part of a broader and more long-standing technological upsurge that poses a number of challenges to labour market institutions, that is labour market policies and systems of skills generation (Eichhorst & Rinne, 2017). As digitalisation also drives changes across various industries and occupations, digital skills are increasingly recognized as essential for employment prospects in nowadays advanced countries.

According to the liberal theory of modernisation, processes of technological innovation have deeply transformed the occupational distribution of Western countries by decreasing the proportion of people engaged in agriculture and shifting the occupational distribution from the production of goods to the provision of services, thus generating entirely new occupations (Bell, 1973; Treiman, 1970). Similarly, early economic research indicates that the process of technological change that originated in the 1970s has been largely "skill-biased", thereby increasing the opportunity and demand for highly educated workers (Acemoglu, 1998, 2002; Autor et al., 1998; Goldin & Katz, 2007) as computer technology is complementary with human capital. Despite important differences, both liberal theory and skill-biased technological change (SBTC) theory predict that a burst of new technology will cause a profound transformation of the distribution of job tasks in production activities, independently from the sector, thus increasing the demand for highly educated and skilled workers – even more so if endowed with digital

[2] The literature tends to use 'digitalisation' and 'technological innovation' as synonyms. In fact, the latter should indicate the dynamic and processual nature of the process of digital change. However, since in this contribution we do not focus on the temporal development of digitalisation, we can speak of them as de facto synonyms.

competences – and should, in turn, lead to an overall upgrading of both the wage distribution and the occupational composition by shifting employment from low-level, routine-intensive occupations to high-level, highly-waged, knowledge-intensive ones (Autor et al., 1998; Berman et al., 1993; Bound & Johnson, 1992).

However, socio-economic research points out a rise in the proportion of workers employed not only at the top but also at the bottom levels of the occupational structures as a consequence of technological transformations (Autor & Dorn, 2013; Feigenbaum & Gross, 2024; Goos et al., 2009, 2014). Routine-biased technological change (RBTC) theory argues that technologies mainly act as substitutes for explicit and codifiable "routine-task" operations (Autor et al., 2003). However, when it comes to identifying the winners of the technological race, RBTC too predicts a wage premium paid to digital and technological competences.

While both SBTC and RBTC perspectives offer important theoretical insights into understanding the relationship between technological change, digital skills, and employment composition, much less attention has been paid to empirically demonstrate the *causal* link between digital competences and workforce employability within the job matching process. Put differently: do digital skills constitute such a valuable and sought-after form of "digital capital" in the labour matching process? Recent evidence (Pichler and Stehrer, 2021) highlights that possessing adequate digital skills significantly correlates with better job opportunities and higher wages in the EU. However, the evidence relies on cross-sectional survey data (PIAAC and EU-SILC) and makes it difficult to conduct a causal assessment of the impact of digital skills. Additionally, the scarcity of comparative experimental studies on the role of digital skills in the job matching process hampers the possibility of analysing the institutional conditions under which employers' preferences are formed (Di Stasio & Lancee, 2020).

These are precisely the points where our empirical input becomes pertinent. The purpose of this study is twofold. First, we intend to explore whether and to what extent demand-side actors, namely employers and HR managers, evaluate digital competences – as a specific form of human capital – in their screening procedures. In the existing literature, there appears to be more information on the supply of digital skills among the workforce (see, e.g., Cutuli & Tomelleri, 2023) than on its demand, possibly due to the lack of suitable data. As employers are the gatekeepers to the labour market (Bills et al., 2017), it becomes extremely relevant to pay explicit attention to their decision-making processes, which are crucial to the positioning of differently skilled job seekers in the labour market. Ultimately, understanding how recruiters evaluate digital skills is also relevant from a policy perspective, especially for tailoring vocational training programs.

Side by that, our study pointedly contributes to experimental research on the relevance of digital competencies in getting a job by conducting a harmonised cross-country factorial survey experiment on employers' hiring intentions based on candidates' digital skills and by focusing on three contexts with relevant differences in their institutional settings.

Our research is significant for various reasons. First, digitalisation and the introduction of information and communication technologies in manufacturing and services are keys for work productivity improvements in Europe. Exploring how digital and technological skills are evaluated by recruiters is equivalent to digging into one of the main factors that help the European economy keep its competitiveness vis-à-vis other major global competitors, like the US, Japan, or China.

Second, a factor that is rarely considered in the economic literature has to do with the broader economic and institutional environment in which technology is introduced, particularly the average amount of technological competences – thus, a specific component of the general human capital of the workforce that the educational and training systems, which are strongly country-specific, provide to the labour supply. Via the adoption of experimental methods and the comparison of different European countries, we are able to assess how recruiters in distinct shareholder/stakeholder firms' environments, innovative milieus, and production regimes evaluate the workforce's digital competences, and therefore to analyse the distribution of opportunities in the present labour markets situation.

In line with the literature on the institutional embeddedness of labour markets (Barbieri, 2009; Boeri et al., 2012; Eichhorst & Marx, 2010; Maurice et al., 1986), and more specifically on the interplay of educational systems and labour market configurations in shaping employment outcomes (Breen, 2005; Brzinsky-Fay, 2017; Scherer, 2005; Wolbers, 2007), we consider Germany, the United Kingdom, and Italy, each characterised by a specific combination of degree of *labour market dualisation* (Barbieri & Cuteli, 2016; Bentolila et al., 2020), *type of educational* *system* (vocational versus generalistic, see Glauser & Becker, 2016), degree of *skill specificity versus transferability* spurred by the national system of skill formation (Estevez-Abe et al., 2001) and institutions that favour *radical versus incremental innovation* (Hall & Soskice, 2001). We posit that the combination of these macro dimensions originates ideal-typical “institutional configurations” shaping the relevance and therefore the impact of technological innovation and digital competences on labour matching and occupational outcomes.

Germany represents the ideal-type of coordinated market economy, with a firm/industry-based skills regime (Estevez-Abe et al., 2001), a regulated labour market that encourage companies to see employees as a fixed rather than as a variable cost, a diffused system of corporatist wage bargaining side by a great use of long-term bank finance. All these characteristics support *incremental innovation* (Hall & Soskice, 2001), while the dual educational system and the conferral of professional certifications (Damelang et al., 2019) keep the role of digital skills relatively less important in relation to formal educational and vocational attainment.

On the contrary, in the UK liberal market economy, based on the combination of a highly flexible labour market, a generalistic and scarcely differentiated educational system unable to provide firms with clear signals about individuals’ productivity and competences, and a productive system rooted in advanced services in the digitalised tertiary sector that builds its competitive advantage on radical innovation (Manning, 2004; OECD, 2020; Oesch & Rodríguez Menés, 2011), the payoff of digital skills, in terms of employability, can be expected to be way higher than in Central and Southern European contexts.

In Italy, a mixed market economy (Hassel & Palier, 2023; Molina & Rhodes, 2007), we expect the impact of digital competences in the job matching process to be much lower than in the UK and not too dissimilar from the German case, even if for different institutional and structural considerations. Firstly, because of the peculiar dual labour and economic structure that characterises the Italian national economic system; secondly, because of the prevailing business demography, largely oriented towards micro-enterprises, often family-owned, “structurally” less interested in both (highly) skilled labour and high-technology innovation (Burroni et al., 2020, 2022) and less attractive, in terms of wages, for skilled workers. In fact, comparative research signals how Italy scores relatively low, compared to Germany and the UK, when considering returns to education (Heinrich & Hildebrand, 2005).

3. Research questions

Our primary aim in this contribution is that of evaluating the relevance of the (different levels of) digital competences possessed by job applicants and evaluated by employers when filling a vacancy. Accordingly, the first research question we aim to answer is:

> ***RQ1.*** *Do different levels of digital skills of job candidates affect their employability?*

A firm's decision to fill a vacancy with a suitable applicant depends on various aspects, including the characteristics of the applicant and the type of vacant position, and may differ between various occupations. Among the various characteristics of occupations, looking for differences in the payoff of digital competences between high- and mid-level occupations is relevant for many reasons. High-level occupations include service class or technical (Oesch, 2006) positions, managerial professions, and socio-cultural occupations. These occupations require advanced digital skills, including managing complex software, analysing data, and mastering sophisticated digital systems. In contrast, mid-level occupations include lower white collar and lower technical positions, which require basic digital literacy, such as using office software or operating standard digital tools. In this sense, and in accordance with the SBTC literature, intermediate and especially advanced digital skills could significantly increase the employment chances of candidates for higher occupational positions, compared to mid-level positions. With the aim to contribute to this strand of literature, our second question asks:

> ***RQ2.*** *Are there differences in the employability payoff of digital skills between high- and mid-level occupations?*

Digital skills may also exert a different impact depending on the other characteristics of job applicants. A classic human capital measure that exerts a significant effect on hiring (intentions) chances is education (Heckman et al., 2006; Piopiunik et al., 2020). In our contribution, also considering the focus on different occupational levels, we are interested in educational levels and their match or mismatch with the job vacancy. In situations of mismatch between educational and occupational level, digital skills may exert a stronger positive "compensatory" effect on hiring intentions, compared to situations where there is match between educational and occupational level. To shed light on this aspect, our third research question asks:

> ***RQ3.*** *Are there differences in the effect of candidates' digital skills on their employability in situations of match and mismatch between educational and occupational levels?*

As noted previously, the macro-institutional context is likely to shape the role of digital skills for employability, as well as their differential relevance according to occupational level and educational/occupational (mis)match. Our research questions are thus to be understood in the different institutional contexts of Germany, the UK, and Italy. This comparative perspective represents one of the main contributions of our research design compared to the existing studies on the topic.

4. Research design and analytic strategy

To address our research questions, we designed, pre-registered (anonymised citation), and implemented a cross-country factorial survey experiment, which enabled us to manipulate the attributes of theoretical interest in fictitious vignettes (i.e., profiles' descriptions), primarily educational level and digital skills. Factorial survey experiments represent a well-suited method to validly examine recruiters' judgements and beliefs. In existing research, this method has been used for understanding employers' recruiting preferences and the role played by job candidates' education in this respect (Di Stasio, 2014b; Levels et al., 2014).

We relied on the pool of participants provided by Doxa, a data collector realising web surveys and web-based experimental surveys for academic institutions. We selected only recruiters and/or HR managers with recruiting experience, a selection that enabled us to maximise the external validity of our study compared to laboratory experiments or survey experiments relying on samples of, e.g., students. We further checked the recruiting experience of the respondents by asking four filter questions at the beginning of the survey inquiring their experience in different recruiting tasks (see also Mari & Luijkx, 2020; Zamberlan et al., 2024). Specifically, we asked respondents whether they (1) have ever taken part in any phase of the recruitment process such as screening of CVs, job interviews, etc.; (2) ever had the responsibility to hire or fire employees; (3) ever had the responsibility to set or influence the rate of pay received by employees; and (4) ever had an influence on or decided over the promotion of employees. We excluded from the survey respondents who stated that they have no experience in any of these tasks. Respondents received a monetary compensation for fully completing the questionnaire. To ensure a good quality of responses, respondents had to pass an attention check consisting of an evaluation task (i.e., an additional vignette) with precise instructions on how to rate it to successfully complete the survey.

The respondents were told that we were interested in professional careers in each country's labour market and wanted to know their opinion on the best profiles for a job vacancy. They were then presented with short texts (vignettes) describing fictitious job candidates with varying attributes applying to different occupations. An example of vignette text is as follows (dimensions' levels which randomly varied across vignettes are here underlined):

> *Among the applicants, there is a <u>35-year-old</u> <u>woman</u> born in the UK. She is currently looking for full-time employment as an <u>administrative employee and bookkeeper</u>. The applicant obtained a <u>secondary school diploma</u> in accountancy in the UK and has <u>basic software skills</u>[3] (e.g., computer literacy, e-mail communication, internet, elementary database management). <u>She has no significant previous unemployment records</u>. According to a reference letter from her last employer, she is highly motivated and provides good professional performance.*

Table 1 illustrates the dimensions and levels that we randomly varied in the vignettes. Regarding the occupation the candidate is applying for, we selected sectors particularly affected by digital change in the last decades and opted for occupations which are largely representative of each sector. Furthermore, we ensured they cover different occupational levels (business services and administration manager, and industrial and production engineer as high-level occupations, administrative employee and bookkeeper, and mechatronic technician as mid-level occupations), involving different amounts of expected use and knowledge of digital competences.

[3] In the survey, we have opted for the more straightforward term "software skills" ("Softwarekenntnisse" in German, "competenze informatiche" in Italian), with practical examples in brackets to ensure a high internal validity of this dimension of interest.

Table 1. Dimensions and levels varied in the vignettes.

Dimensions	Levels
Gender	1) Male
	2) Female
Age	1) 35 years old
	2) 45 years old
Education	1) Secondary school diploma (secondary plus vocational in Germany) in a field aligned with the sector of the job vacancy
	2) Tertiary education in a field aligned with the sector of the job vacancy
Occupation the candidate is applying for	1) Business services and administration manager
	2) Industrial and production engineer
	3) Administrative employee and bookkeeper
	4) Mechatronic technician
Digital skills	1) Basic (computer literacy, e-mail communication, internet, elementary database management)
	2) Intermediate (some programming skills, use of on-board diagnostics software, knowledge of CAD/CAM systems, use of technical/statistical software)
	3) Advanced (advanced programming language capabilities, expert use of cloud computing platforms, expertise with big data management, advanced knowledge of scientific/statistical software, advanced CAD/CAM, and robotics programming skills)
Previous unemployment experience	1) Has no significant previous unemployment records
	2) Has been previously unemployed for about 12 months

For each vignette, that is, for each fictitious job candidate, respondents were asked to indicate, on a 0-10 scale (in line with previous experimental research on the topic, see Auspurg & Hinz, 2015), how likely they would be to (1) invite the applicant to an interview, (2) shortlist the person for the job, and (3) hire the candidate.

Considering the number of dimensions' levels, the vignettes' universe is equal to 192 (2*2*2*4*3*2). As we planned to have a number of respondents in each country higher than the vignette universe, we opted for a fully randomised experimental design, in which we split the vignettes' universe into 32 different decks, each composed of 6 randomly picked vignettes. 6 represents an optimal number of vignettes to ensure within-respondent variability without generating fatigue effects (Auspurg & Hinz, 2015). Every respondent was randomly assigned one of these 32 decks and evaluated the 6 vignettes. We further ensured that each deck appeared to respondents a balanced number of times.

After completing the vignette task, respondents were asked to complete a questionnaire that collected useful socio-demographic information and details of the respondent's and their organisation's level of digital literacy.

The number of participants is equal to 702 in Germany and Italy, and 703 in the UK. We dropped 26 respondents who completed the survey in more than 55 minutes (99th percentile of the survey duration distribution). We checked for illogical responses, i.e., respondents who gave a higher score for hiring than for shortlisting or calling back the candidate, finding only one respondent giving low quality answers according to this criterion. We then checked for constant answer behaviour, namely respondents who gave the same score to all vignettes in all three dependent variables, dropping 104 respondents. The final analytic sample is thus composed of 1,976 respondents (653 in Germany, 665 in the UK, and 658 in Italy) and a total of 11,856 observations.

Answers given by respondents to the survey provided a database with matched information on respondents and fictitious job candidates. Based on this information, we investigated to what extent different levels of candidates' digital skills influence recruiters' evaluations and whether such effect varies by occupational level, educational/occupational (mis)match, and country. We relied on multilevel models with random intercepts where vignettes (level 1 – *i-th* vignette) are nested within respondents (level 2 – *j-th respondent*). The random-intercept multilevel model is the standard method for analysing survey experimental data where responses to vignettes are nested within respondents (Auspurg and Hinz, 2014). This method enables us to test how vignette characteristics (X_{ij}) affect candidates' employability (Y_{ij}). We run models including all vignette dimensions jointly, as well as respondents' characteristics (Z_j). The model is structured in the following way:

$$Y_{ij} = \beta_0 + \beta_i X_{ij} + \beta_k Z_{jk} + u_j + e_{ij}$$

$$e_{ij} \sim N(0, \sigma_e^2)$$

$$u_j \sim N(0, \sigma_u^2)$$

where β_0 represents the average intercept across all groups, β_i is the coefficient for the *i-th* vignette characteristic X_{ij} across all *j* respondents, β_k is the *k* coefficient for the group-level covariate Z_j, u_j is the deviation of the *j-th* group's intercept from the overall average β_0, and e_{ij} represents the independent and identically distributed residual error term at the vignette level. In our model, u_j represents the random intercept for group *j*, capturing the group-level variation. u_j and e_{ij} are normally distributed with mean 0 and variance σ_e^2 and σ_u^2.

Considering the absence of significant differences in the main effects by the different dependent variables (namely intentions to callback, shortlist, and hire – see figure A1) and to provide a parsimonious presentation of the results, we only focus on hiring intentions. This choice is further supported by the greater relevance of this dependent variable compared to the others. Although still in the realm of recruiters' intentions, hiring has a much stronger impact on labour market outcomes than the previous steps in the recruitment process and is therefore arguably the most relevant and interesting variable to analyse.

In our study, the X_i vignette characteristics include gender, age, and previous unemployment experience. The level of digital skills (basic, intermediate, or advanced) is the main explanatory variable of interest. Education is used as an explanatory variable whose effect is compared with that of digital skills in the first set of results (section 5.1) and as a moderator in the last set of results (section 5.3). The occupation for which the candidate is applying is used as a moderator (i.e., interacted with digital skills in section 5.2, and with digital skills and education in section 5.3). The models also include survey characteristics, such as the length of the survey and the order of the vignettes presented to respondents, as well as a number of respondent characteristics, such as their gender, age, education level, country of residence, nationality, employment status, occupation, sector, number of employees in their current company, whether the respondent has subordinates, the respondent's self-assessed level of digital skills, the average level of digital skills in the respondent's current company, the type of recruiting experience the respondent has, and whether the sector in which the respondent has recruiting experience matches the sector shown in the vignette. This last variable is computed at the vignette level. Finally, models that pool all country observations include a country dummy.

5. Results

In this section, we first present the results related to the single effect of digital skills levels on recruiters' hiring intentions (RQ1), followed by a comparison with the effect of the level of education of the fictitious candidates on their employability. We then consider the gradient to which digital skills could be a boost for employability in high and mid-level occupational positions (RQ2) by interacting the candidate's level of digital skills and the occupational level (s)he is applying for. Finally, we investigate the role of digital skills on employability in situations of match or mismatch between the position the candidate is applying for and their formal educational level (RQ3). In practice, we interact candidates' digital skills with a variable that combines their level of education and the occupational position they are applying for. With the aim to test our hypotheses and explore cross-country variability, we report average marginal effects (henceforth AME), first overall (in graphical form) and then by country (in tables).

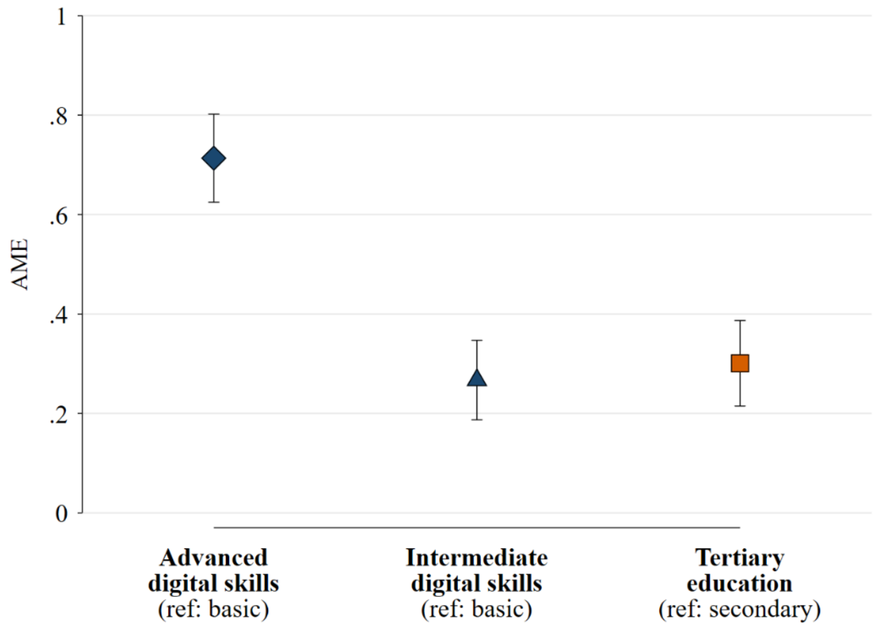
5.1 Digital skills as a boost to employability

Figure 1 shows the AME of the fictitious candidates' digital skills level (advanced and intermediate, as opposed to basic) and tertiary education (rather than secondary education) on the recruiters' stated likelihood of hiring them (the original scale ranges from 0 to 10). The coefficients should be interpreted as the expected change in hiring intentions for a unit increase in the predictor variable.

We observe a clear and significant impact of digital competences on job seekers' chances of being hired. The strongest effect is observed for candidates with an advanced level of digital skills (i.e., advanced programming language skills, expert use of cloud computing platforms, expertise in large data management, advanced knowledge of scientific/statistical software, advanced CAD/CAM and robotics programming skills), for whom employability chances increases by 7.1% (b=0.71) compared to candidates with basic digital skills. Intermediate digital skills (i.e., having some programming skills, using on-board diagnostic software, having knowledge of CAD/CAM systems, using technical/statistical software) increases employability chances of a fictitious candidate by 2.7 % (b=0.27) compared to having basic skills. Interestingly, this effect is similar in magnitude to that of possessing a tertiary education degree, i.e., 3 % (b=0.30).

In general, what emerges from figure 1 is that, in the recruitment process, digital skills appear to boost employability even more than educational attainment, as long as these skills are particularly advanced.

Figure 1. Average marginal treatment effects of digital skills level and education on recruiters' hiring intentions. All countries pooled.



N: 1,976 respondents (11,856 observations).

Interesting differences between institutional contexts emerge when looking beyond the overall role of education and level of digital skills in the recruitment process. Table 2 shows the effects of digital skills levels and education of the fictitious candidates on recruiters' stated likelihood to hire the candidate for each of the three labour markets (countries) considered in our analysis. For the sake of simplicity, we only report the effects of the variables of interest; complete regression results are reported in the appendix (Table A2).

The effect of having an advanced level of digital skills is the largest effect in magnitude in all the three countries, confirming what shown in Figure 1. It reaches 1.021 (or 10.21 %) in the UK and is about half as high in Germany and Italy (0.533 and 0.556 respectively, or 5.33 and 5.56 %). Intermediate digital skills turn to be more recognised in the UK, with an increase in recruiters' hiring intentions by 0.518, a similar level seen for advanced skills in the two European continental countries. In Germany and Italy, the effect of intermediate digital skills is generally smaller (it ranges from 0.133 to 0.137 respectively) and partly loses statistical significance.

The effect of tertiary education is particularly high in Italy (0.458), while we observe similar magnitudes in the UK (0.197) and in Germany (0.221). Despite this, in comparison to intermediate digital skills, both in Germany and in Italy the effect of tertiary education is larger than the effect of intermediate digital skills in shaping recruiters' hiring intentions.

Table 2. Average marginal treatment effects of digital skills level and education on recruiters' hiring intentions, by country.

Variable	Level	(1) UK	(2) Germany	(3) Italy
Digital skills	advanced	1.021***	0.533***	0.556***
		(0.087)	(0.073)	(0.071)
	intermediate	0.518***	0.133*	0.137*
		(0.078)	(0.067)	(0.064)
Education	tertiary	0.197*	0.221**	0.458***
		(0.079)	(0.076)	(0.070)
N Vignettes		3,990	3,918	3,948

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

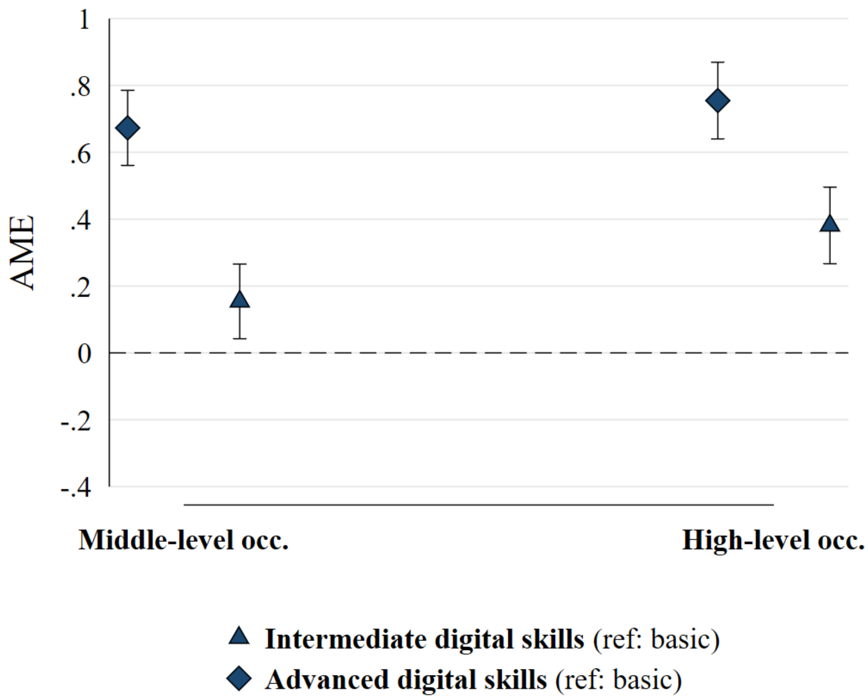
5.2 Heterogeneity by occupational level

Having assessed the positive effect of digital skills on recruiters' hiring intentions, we are now interested in whether the occupation for which the candidate is applying makes a difference in terms of evaluation of the digital competences We chose to group the different occupations according to their level, in line with the routinisation literature: engineering and managerial vacancies were grouped in the same category and referred to as high-level occupations, while clerk and technical vacancies were grouped in the mid-level occupational categories.

Figure 2 shows the overall AME of having advanced or intermediate digital skills compared to basic skills on recruiters' hiring intentions, separately for medium and high-level occupations. Overall, the higher the level of digital skills possessed, the higher the employability of the fictitious candidate, for both medium and high-level occupations. Looking at the effect of advanced digital skills on hiring intentions, it is positive, statistically significant, and larger than the effect of intermediate skills in both middle- and high-level occupations. The AME of advanced skills is 0.67 for medium-level occupations, while it is 0.76 for high-level occupations. The difference between the effect of advanced digital skills in middle- and high-level occupations is not statistically significant ($p=0.261$), meaning that having advanced digital skills always increases the chances of being hired, regardless of the level of the occupations for which applicants are applying.

A different picture emerges when looking at intermediate digital skills: these skills are more valuable when applying for high-level job positions. The AME of intermediate digital skills is 0.15 for medium-level occupations, while it is 0.38 for high-level occupations, a difference that turns to be statistically significant ($p<0.01$).

Figure 2. Average marginal treatment effects of digital skills level on recruiters' hiring intentions, by occupational level. All countries pooled.



N: 1,976 respondents (11,856 observations).

Table 3 shows the AME of digital skills on hiring chances by occupational level, for the three different countries. Possessing advanced digital skills exerts a larger positive effect overall, confirming the pattern observed in figures 1 and 2, but with a larger magnitude in the UK and similar smaller magnitudes in Germany and Italy. As seen in the aggregate model (Figure 2), there is no substantial difference between the effect of advanced digital skills in middle and high-level occupations within countries. Regarding the role of intermediate skills, their positive effect on employability is consistently larger in the UK than in Germany and Italy, as observed in the previous section. Furthermore, effect sizes are quite small and do not reach statistical significance in the two continental European countries for what middle-level occupations are concerned.

In general, across all three countries, there is a consistent pattern where advanced digital skills significantly increase candidates' hiring chances with no significant difference across occupational-level groups within countries. While AMEs are higher for the UK, an intermediate skill level does not provide a substantial or significant advantage in Germany and Italy, where the two coefficients are small and not statistically significant for mid-level occupations. In sum, as expected, when investigating country differences, the boost of digital skills is less pronounced in continental European countries, especially for what middle-level occupations are concerned.

Table 3. Average marginal treatment effects of digital skills level on recruiters' hiring intentions, by occupational level and country.

Digital skills level	(1) **UK**	(2) **Germany**	(3) **Italy**
	high-level occ.		
advanced	1.039***	0.568***	0.629***
	(0.113)	(0.097)	(0.092)
intermediate	0.707***	0.193*	0.224*
	(0.112)	(0.088)	(0.101)
	middle-level occ.		
advanced	1.005***	0.497***	0.483***
	(0.112)	(0.092)	(0.089)
intermediate	0.330**	0.072	0.053
	(0.108)	(0.095)	(0.089)
N Vignettes	3,990	3,918	3,948

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

5.3 Digital skills: a compensating mechanism for educational/occupational mismatches?

Previous findings pointed to the significant role of fictitious candidates' educational level on recruiters' hiring intentions in continental European countries such as Germany and Italy. Digital skills are of relatively less importance when formal educational competences are more firmly established and certified, as in Germany and – although for different reasons – in Italy. Notably, in these contexts, the impact of tertiary education on employability appears to outweigh that of intermediate digital skills, as shown in Table 2. This finding underlines the importance of jointly considering education, digital skills level, and occupational level to better understand the employability of different candidates' profiles.

To better understand the role of digital skills for different combinations of candidates' educational qualifications and job levels, we leveraged the orthogonal nature of the vignette dimensions, whereby a candidate with a tertiary education title could apply for both a high-level job (manager or engineer) and a middle-level job (clerk or technician), in the latter case being *overqualified*. Conversely, a candidate with a secondary education qualification could apply for a middle-level job or a high-level job, in the latter case being *underqualified*. Table 4 illustrates the possible combinations of candidates' educational qualifications and occupational levels.

Table 4. Combinations of educational and occupational levels.

Educational level	**Occupational level**	
	Intermediate	High
Secondary school diploma	Match: mid-level	Underqualified
Tertiary education	Overqualified	Match: high-level

Note: Intermediate-level occupational level stands for administrative employee and bookkeeper or mechatronic technician, while high-level occupational level stand for business services and administration manager or industrial and production engineer.

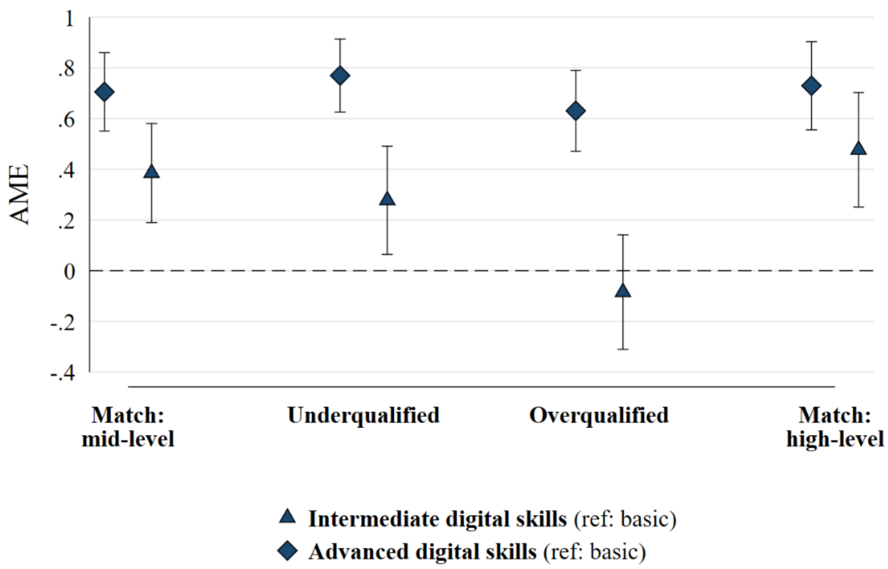
Figure 3 shows the AME of having intermediate or advanced digital skills, as opposed to basic skills, on recruiters' hiring intentions for each of the four combinations of candidate education and occupational level.

Having advanced digital skills rather than basic skills has a positive and statistically significant effect on recruiters' hiring intentions, which is consistent and of similar magnitude (from 0.63 for overqualified candidates to 0.77 for underqualified ones, with no statistically significant differences between the estimates) across the different combinations of candidates' educational qualifications and occupational level. Advanced digital skills thus have a strong and consistent positive effect on employability regardless of the educational level of the candidates and the occupational level to which they apply.

Looking at the effect of intermediate digital skills on employability, a positive and statistically significant effect clearly emerges in cases where the candidates' educational qualifications and occupational level correspond. This effect is 0.38 for a mid-level match and 0.48 for a high-level match.

The differences among intermediate and advanced digital skills emerges when a mismatch occurs. The effect of intermediate digital skills (b=0.28) is still significantly different from that of basic digital skills in the case of applicants who are underqualified for a vacancy (i.e., who have secondary education but are applying for a high-level job), albeit with an effect of lower magnitude compared to when there is a match between educational attainment and occupational level. Instead, the effect of intermediate skills is no different from that of basic skills for overqualified applicants. The latter finding may indicate a penalty that recruiters impose on highly educated candidates (with intermediate digital skills) applying for a mid-level job, possibly because being overqualified carries a negative signal.

Figure 3. Average marginal treatment effects of digital skills level on recruiters' hiring intentions, by educational/occupational (mis)match. All countries pooled.



N: 1,976 respondents (11,856 observations).

Looking at the cross-country differences illustrated in Table 5**,** the effect of possessing advanced skills rather than basic ones appears large and statistically significant for all the four groups of educational/occupational (mis)match in the UK, ranging from 0.97 to 1.12. The effect of advanced digital competences is generally halved in the continental and southern European countries considered, although with country-specific peculiarities. Even if the effects of advanced digital skills for the different educational/occupational groups is not statistically different within-country[4], in Germany recruiters tend to give greater importance to advanced digital skills of underqualified candidates. In Italy, advanced digital skills have the lowest importance when possessed by overqualified candidates.

Regarding intermediate digital competences, there seem to be no major compensation or boost effects across educational/occupational combinations, with interesting country-specific patterns.

[4] The Wald test on the null hypothesis that all the coefficients are simultaneously equal fails to reject the null hypothesis (p-value=0. 619 for Germany 0.184 for Italy).

In the UK, intermediate digital skills have a statistically significant effect in the case of a high-level educational/occupational match (0.787) and of underqualified candidates (0.628). In Germany, intermediate digital skills have an effect of smaller magnitude compared to the other countries, which does not reach statistical significance. In Italy, intermediate digital skills exert a statistically significant effect on employability only in the case of a match between the educational level and the position for which the candidate is applying (0.388 for the high-level match and 0.495 for the mid-level match). Interestingly, intermediate digital skills have a negative effect in this context if the candidate is overqualified (a negative coefficient is also found for Germany, but it does not reach statistical significance), possibly indicating that having better digital skills than the basic level, although not enough to reach the advanced level, may entail a further penalty for candidates who are already too highly educated compared to the occupational level they are applying for.

Table 5. Average marginal treatment effects of digital skills level on recruiters' hiring intentions, by educational/occupational (mis)match and country.

	(1) **UK**		(2) **Germany**		(3) **Italy**	
match/digital skills	high/high	mid/mid	high/high	mid/mid	high/high	mid/mid
advanced	0.970***	0.986***	0.455**	0.492***	0.723***	0.595***
	(0.174)	(0.146)	(0.141)	(0.126)	(0.142)	(0.135)
intermediate	0.787***	0.312	0.208	0.302	0.388*	0.495***
	(0.205)	(0.186)	(0.191)	(0.175)	(0.190)	(0.146)
mismatch/digital skills	overq.	underq.	overq.	underq.	overq.	underq.
advanced	1.036***	1.117***	0.487***	0.670***	0.348**	0.513***
	(0.166)	(0.142)	(0.132)	(0.127)	(0.112)	(0.109)
intermediate	0.351	0.628**	-0.163	0.174	-0.407*	0.043
	(0.205)	(0.195)	(0.203)	(0.183)	(0.176)	(0.179)
N Vignettes	3,990		3,918		3,948	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

6. Discussion and Conclusions

Over the past decades, economic, social, and industrial changes have significantly influenced the need for digital skills in the labour market. Digital skills are now considered essential as they help workers to be more adaptable in meeting work-related challenges and responding to changes in demand for goods and services, ultimately increasing their employability. It is therefore crucial to understand if and how the possession of certain levels of digital skills affects the employability of jobseekers. However, to the best of our knowledge, existing research on this topic lacks a causal test of digital skills on employability. Moreover, the interplay between digital skills and education, and its heterogeneity across occupational levels, is a generally overlooked area of research.

In this contribution, we aimed to provide new evidence on the causal effect of digital skills on employment opportunities, their interaction with educational attainment, and for different occupational levels. We did so by conducting a cross-national factorial survey experiment on the topic in three European contexts that differ in their education and labour market systems, namely Germany, Italy, and the United Kingdom.

Our results showed that digital skills consistently improve employability, as reported by recruiters in the three countries, across different profiles of jobseekers (RQ1). This is the case whether we are talking about high-level or middle-level jobs (RQ2), and even in the case of mismatches between educational and occupational levels (i.e. under- and over-qualified candidates) (RQ3). Interestingly, an advanced level of digital skills enhances employability even more than a classical human capital qualification such as educational level.

At the country level, digital skills in the UK are consistently associated with higher employability, even at intermediate levels. These skills are even more relevant to UK recruiters than a tertiary degree. Given the institutional characteristics of the UK context, this result can be explained by the broad and minimally stratified UK education system (Hadjar & Gross, 2016), which provides limited information about the productivity and skills of individuals. The limited relevance of educational qualifications is likely to be exacerbated by a production model focused on advanced services in the digitalised tertiary sector (Manning, 2004; OECD, 2020; Oesch & Rodríguez Menés, 2011).

Germany and Italy show similar patterns in all analyses carried out, where educational qualifications still have a strong impact on employability, even overshadowing the influence of (intermediate) digital skills. Moreover, in situations of mismatch between educational qualifications and occupational level, intermediate skills are not valued more than basic skills and, in some cases, recruiters tend to penalise the candidate for possessing a more-than-basic level of digital skills (as observed in Italy for overqualified candidates). However, these country similarities are probably due to different dynamics. In Germany, the dual education system makes educational qualifications and certifications a central element in the selection of candidates (Damelang et al., 2019). In Italy, the economic fabric, consisting mainly of micro and small (family-owned) enterprises operating mainly in low-technology sectors such as sub-contracting in the manufacturing, or low-knowledge-intensive services (Burroni et al., 2020, 2022), still tends to rely more on formal education as the main signal of labour productivity.

Our findings underline the complex interplay between digital skills, educational qualifications, and labour market dynamics in determining employability, and highlight the nuanced impact of these factors in different institutional contexts. Most importantly, they suggest that in rapidly evolving fields such as technology, there is often a high demand for hyper-specific skills; if a worker possesses the latest and most in-demand digital skills, he or she can be hired even with a lower level of formal education. These findings provide valuable input for labour and training policy recommendations. At the same time, however, an adequate consideration of the institutional embeddedness of the process of matching labour demand and supply in times of sustained technological change is highly relevant. While providing a new, comparative experimental evidence on this timely topic, we hope that a growing number of studies will extend our knowledge by varying and expanding the contexts, occupations, and types of digital skills analysed.

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Appendix

Table A1. Descriptive statistics of respondents by country and on the total sample

	Country			
	Germany	**United Kingdom**	**Italy**	**Total**
N	653 (33.0%)	665 (33.7%)	658 (33.3%)	1,976 (100.0%)
Gender				
man	414 (63.4%)	375 (56.4%)	439 (66.7%)	1,228 (62.1%)
woman	236 (36.1%)	289 (43.5%)	219 (33.3%)	744 (37.7%)
else	3 (0.5%)	1 (0.2%)	0 (0.0%)	4 (0.2%)
Respondent Age	43.377 (13.100)	42.841 (13.576)	42.796 (10.833)	43.003 (12.559)
Educational Level				
primary or lower	82 (12.6%)	7 (1.1%)	110 (16.7%)	199 (10.1%)
secondary	248 (38.0%)	234 (35.2%)	303 (46.0%)	785 (39.7%)
tertiary or more	323 (49.5%)	424 (63.8%)	245 (37.2%)	992 (50.2%)
Country				
same of residence	632 (96.8%)	595 (89.5%)	645 (98.0%)	1,872 (94.7%)
else	21 (3.2%)	70 (10.5%)	13 (2.0%)	104 (5.3%)
Nationality				
Same of residence	639 (97.9%)	600 (90.2%)	653 (99.2%)	1,892 (95.7%)
foreign	14 (2.1%)	65 (9.8%)	5 (0.8%)	84 (4.3%)
Type of occupation				
employee	503 (77.0%)	471 (70.8%)	480 (72.9%)	1,454 (73.6%)
self-employed	145 (22.2%)	187 (28.1%)	170 (25.8%)	502 (25.4%)
unemployed	2 (0.3%)	3 (0.5%)	5 (0.8%)	10 (0.5%)
retiree/inactive	3 (0.5%)	4 (0.6%)	3 (0.5%)	10 (0.5%)
Job Position				
manager	277 (42.4%)	338 (50.8%)	152 (23.1%)	767 (38.8%)
professional	171 (26.2%)	146 (22.0%)	224 (34.0%)	541 (27.4%)
clerical support worker	83 (12.7%)	58 (8.7%)	163 (24.8%)	304 (15.4%)
services or sales worker	14 (2.1%)	6 (0.9%)	37 (5.6%)	57 (2.9%)
self-employed	95 (14.5%)	95 (14.3%)	51 (7.8%)	241 (12.2%)
lower supervisory tech.	9 (1.4%)	5 (0.8%)	12 (1.8%)	26 (1.3%)
blue collar	4 (0.6%)	17 (2.6%)	19 (2.9%)	40 (2.0%)

Sector				
Other Services	151 (23.1%)	123 (18.5%)	132 (20.1%)	406 (20.5%)
Manufacturing	138 (21.1%)	104 (15.6%)	107 (16.3%)	349 (17.7%)
Services	358 (54.8%)	431 (64.8%)	410 (62.3%)	1,199 (60.7%)
Agriculture	6 (0.9%)	7 (1.1%)	9 (1.4%)	22 (1.1%)
Firm size				
less than 5	83 (12.7%)	118 (17.7%)	90 (13.7%)	291 (14.7%)
5-20	61 (9.3%)	73 (11.0%)	102 (15.5%)	236 (11.9%)
21-50	91 (13.9%)	97 (14.6%)	114 (17.3%)	302 (15.3%)
51-100	127 (19.4%)	118 (17.7%)	134 (20.4%)	379 (19.2%)
100+	291 (44.6%)	259 (38.9%)	218 (33.1%)	768 (38.9%)
Subordinates under direct control	19.087 (21.528)	16.220 (19.670)	14.600 (17.785)	16.628 (19.792)
Self-assessment of technological competencies				
basic	116 (17.8%)	86 (12.9%)	70 (10.6%)	272 (13.8%)
intermediate	275 (42.1%)	308 (46.3%)	321 (48.8%)	904 (45.7%)
advanced	262 (40.1%)	271 (40.8%)	267 (40.6%)	800 (40.5%)
Workplace technological composition				
basic	45.807 (28.310)	41.940 (28.306)	44.208 (24.294)	43.973 (27.071)
intermediate	31.296 (21.407)	32.829 (21.705)	33.258 (18.171)	32.465 (20.499)
advanced	22.897 (22.219)	25.232 (22.450)	22.533 (16.888)	23.562 (20.706)
Working experience	21.083 (12.646)	20.886 (13.988)	18.760 (10.004)	20.243 (12.368)
Unemployment experience				
yes, short periods	238 (36.4%)	298 (44.8%)	293 (44.5%)	829 (42.0%)
yes, long periods	71 (10.9%)	74 (11.1%)	99 (15.0%)	244 (12.3%)
no	344 (52.7%)	293 (44.1%)	266 (40.4%)	903 (45.7%)
Recruitment experience				
yes, current job	452 (69.2%)	430 (64.7%)	441 (67.0%)	1,323 (67.0%)
yes, previous job	164 (25.1%)	213 (32.0%)	193 (29.3%)	570 (28.8%)
no	37 (5.7%)	22 (3.3%)	24 (3.6%)	83 (4.2%)

Hiring/firing experience				
es, current job	440 (67.4%)	403 (60.6%)	384 (58.4%)	1,227 (62.1%)
yes, previous job	158 (24.2%)	214 (32.2%)	172 (26.1%)	544 (27.5%)
no	55 (8.4%)	48 (7.2%)	102 (15.5%)	205 (10.4%)
Wage setting experience				
yes, current job	381 (58.3%)	392 (58.9%)	334 (50.8%)	1,107 (56.0%)
yes, previous job	136 (20.8%)	170 (25.6%)	177 (26.9%)	483 (24.4%)
no	136 (20.8%)	103 (15.5%)	147 (22.3%)	386 (19.5%)
Promotion experience				
yes, current job	406 (62.2%)	386 (58.0%)	382 (58.1%)	1,174 (59.4%)
yes, previous job	144 (22.1%)	212 (31.9%)	181 (27.5%)	537 (27.2%)
no	103 (15.8%)	67 (10.1%)	95 (14.4%)	265 (13.4%)

Note: When not indicated by the percentage symbol, the number in brackets indicates the standard deviation.

Table A2. Multilevel model estimates hiring intentions, overall and by country – vignette characteristics.

	(1) Total	(2) U.K.	(3) Germany	(4) Italy
man	0.122*	0.168	0.087	0.079
	(0.056)	(0.103)	(0.094)	(0.095)
age 45	0.133*	0.176	0.200	-0.004
(ref. 35)	(0.059)	(0.108)	(0.107)	(0.090)
tertiary educ.	0.301***	0.197*	0.221**	0.458***
(ref. secondary educ.)	(0.044)	(0.079)	(0.076)	(0.070)
intermediate digital skills.	0.267***	0.518***	0.133*	0.137*
(ref. basic DS)	(0.041)	(0.078)	(0.067)	(0.064)
advanced digital skills.	0.713***	1.021***	0.533***	0.556***
(ref. basic DS)	(0.045)	(0.087)	(0.073)	(0.071)
previously unemployed	-0.307***	-0.303***	-0.436***	-0.184**
(ref. no sig. prev. unemp. records)	(0.042)	(0.074)	(0.079)	(0.062)
industrial and production engineer	-0.304***	-0.312	-0.244	-0.302*
ref. business services and adm. manager	(0.089)	(0.162)	(0.153)	(0.151)
adm. employee and bookkeeper	-0.035	-0.034	-0.067	0.060
ref. business services and adm. manager	(0.085)	(0.160)	(0.148)	(0.140)
mechatronic techn.	-0.219***	0.051	-0.514***	-0.204*
ref. business services and adm. manager	(0.059)	(0.100)	(0.118)	(0.081)
duration	0.007	-0.001	0.019*	-0.002
	(0.006)	(0.013)	(0.009)	(0.012)
N Vignettes	11,856	3,990	3,918	3,948
Vignette order controls	yes	yes	yes	yes
Respondent characteristics	yes	yes	yes	yes
State FE	yes	no	no	no

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Continuation of Table A2. Multilevel model estimates hiring intentions, overall and by country – respondent characteristics, part 1.

	(1) Total	(2) U.K.	(3) Germany	(4) Italy
Respondent characteristics				
woman	0.222**	0.095	0.161	0.420**
ref. man	(0.083)	(0.145)	(0.145)	(0.133)
else	-0.448	-1.614***	-0.437	
	(0.416)	(0.451)	(0.516)	
Age	0.014	0.016	0.007	0.024*
	(0.008)	(0.013)	(0.016)	(0.012)
secondary	0.098	2.155*	0.079	0.075
ref primary or lower	(0.151)	(0.911)	(0.241)	(0.173)
tertiary or more	-0.027	2.175*	-0.178	-0.140
ref. primary or lower	(0.157)	(0.907)	(0.255)	(0.186)
else	0.167	-0.097	0.760	0.075
ref. same cntry of resid.	(0.190)	(0.242)	(0.392)	(0.489)
foreign	-0.320	-0.025	-0.835	-1.687**
	(0.229)	(0.276)	(0.468)	(0.591)
self-employed	-0.230	0.018	-0.076	-0.324
	(0.138)	(0.244)	(0.236)	(0.218)
unemployed	-0.026	0.013	-2.025	0.598*
	(0.643)	(0.712)	(1.737)	(0.264)
retiree/inactive	0.025	-0.325	0.195	0.660
	(0.427)	(0.445)	(1.008)	(0.468)
professional	-0.073	-0.078	-0.205	0.074
ref. manager	(0.101)	(0.187)	(0.172)	(0.169)
clerical support worker	-0.096	-0.025	-0.526*	0.160
ref. manager	(0.127)	(0.252)	(0.265)	(0.171)
services or sales worker	0.039	-0.799	-0.081	0.328
ref. manager	(0.219)	(0.824)	(0.397)	(0.252)

Table continued

Continuation of Table A2. Multilevel model estimates hiring intentions, overall and by country – respondent characteristics, part 2.

	(1) Total	(2) U.K.	(3) Germany	(4) Italy
Previous table continued				
self-employed	-0.146	-0.188	-0.425	0.058
ref. manager	(0.188)	(0.287)	(0.354)	(0.319)
lower supervisory tech.	-0.336	-1.270	-0.039	-0.170
ref. manager	(0.312)	(0.694)	(0.376)	(0.457)
blue collar	-0.327	-1.024*	1.457	0.024
ref. manager	(0.294)	(0.470)	(0.995)	(0.321)
Manufacturing	-0.017	-0.547*	0.314	0.123
Other Services	(0.123)	(0.244)	(0.208)	(0.193)
Services	-0.063	-0.244	0.110	-0.051
Other Services	(0.098)	(0.172)	(0.171)	(0.158)
Agriculture	-0.195	-0.584	0.166	0.030
Other Services	(0.520)	(0.770)	(1.137)	(0.736)
Firm size (ref. less than 5)				
5-20	0.063	0.488	0.227	-0.216
	(0.180)	(0.305)	(0.387)	(0.264)
21-50	-0.224	-0.049	0.154	-0.499
	(0.187)	(0.325)	(0.403)	(0.285)
51-100	0.001	-0.162	0.261	0.092
	(0.197)	(0.336)	(0.423)	(0.275)
100+	-0.121	-0.051	0.116	-0.111
	(0.186)	(0.323)	(0.400)	(0.263)
Subordinates	0.005*	0.008	0.002	0.004
	(0.002)	(0.004)	(0.004)	(0.004)
Table continued				

Continuation of Table A2. Multilevel model estimates hiring intentions, overall and by country – respondent characteristics, part 3.

	(1) Total	(2) U.K.	(3) Germany	(4) Italy
Tech. skills reposndent (ref.basic)				
intermediate	0.097	0.064	0.084	0.050
	(0.140)	(0.244)	(0.258)	(0.201)
advanced	0.270	0.186	0.352	0.219
	(0.154)	(0.276)	(0.273)	(0.228)
tech. composition basic	0.001	-0.001	0.001	0.004
	(0.002)	(0.004)	(0.003)	(0.004)
tech composition intermediate	-0.001	-0.007	0.002	0.008
	(0.003)	(0.005)	(0.004)	(0.005)
tech composition advanced	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
unemp. exp	-0.008	-0.019	0.008	-0.023
	(0.008)	(0.013)	(0.016)	(0.012)
yes, long periods	-0.005	0.384	-0.208	-0.189
ref. short period	(0.137)	(0.234)	(0.250)	(0.209)
no	-0.089	-0.195	0.089	-0.235
ref. short period	(0.082)	(0.151)	(0.153)	(0.121)
Constant	6.971***	4.778***	6.744***	6.350***
	(0.417)	(1.173)	(0.742)	(0.621)
lns1_1_1				
Constant	0.401***	0.426***	0.396***	0.245***
	(0.024)	(0.034)	(0.044)	(0.053)
lnsig_e				
Constant	0.633***	0.712***	0.611***	0.535***
	(0.015)	(0.021)	(0.028)	(0.031)
N Vignettes	11,856	3,990	3,918	3,948
Vignette order controls	yes	yes	yes	yes
Recruiting experience controls	yes	yes	yes	yes
State FE	yes	no	no	no

Standard errors in parentheses

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* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1. Average marginal treatment effects of digital skills level and education on recruiters' hiring intentions. All countries pooled.