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In-demand skills: a shield against automation—evidence from online job vacancies

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Abstract

This paper investigates how in-demand skills, advertised wages, and occupational exposure to automation co-evolve in Slovakia's online labor market. Drawing on data covering nearly the full universe of online job vacancies posted in Slovakia in 2022, the analysis extracts skills from unstructured text and maps them into fifteen conceptual categories spanning cognitive, socio-emotional, and manual domains. These categories account for a sizeable share of wage variation, with several linked to notable premia or penalties. Automation risk is gauged through a novel Europe-specific measure of exposure to AI and machine learning, software, and robotics, constructed by matching patent text to task-level occupational descriptions in a shared semantic space. First, the analysis examines whether the conditional number of in-demand skills differs across firms that are more tilted toward adoption of automation technologies, proxied by the occupational structure of their labor demand. The evidence reveals a non-monotonic pattern: vacancies posted by firms more exposed to AI and software list more skills, whereas those concentrated in robotics-exposed roles list fewer; across technologies, skill demand peaks at intermediate adoption levels, forming a clear hump shape. Analysis of skill composition and automation exposure shows that bundles demanding abstract and manual abilities—people and project management, software-specific, financial, hand–foot–eye coordination—are correlationally associated with lower exposure, while clusters featuring routine cognitive, customer-service, and social or character skills align with higher exposure, indicating complementarity. Estimates of average treatment effects confirm a negative association between abstract and manual skills and automation exposure, supporting the view that such capabilities act as a shield against automation. Routine and socio-emotional skills, by contrast, remain concentrated in highly exposed occupations, consistent with their complementary role in tasks that evolve alongside new technologies.

Keywords Automation, Labor demand, Patents, Online job vacancies

JEL Classification E24, J23, J24, J31, J63

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1 Introduction

Technological change and advances in automation technologies have the potential to completely disrupt traditional work. Skills are essential for performing tasks in the production process, where labor competes with capital for optimal efficiency in task production (Acemoglu and Restrepo 2018). The more complex the skills that labor possesses–enabling the production of more complex tasks–the less susceptible it is to automation by capital, and vice versa. Therefore, some skills may act as a shield against automation. An important empirical limitation in studying technological change is that most data sources capture between-occupational task variation but overlook variation within occupations (Deming and Kahn 2018).

This paper addresses this limitation by examining the composition of in-demand skills within occupations, as revealed through firms demand in online job vacancies. I deliberately focus on skills rather than occupations for three main reasons. First, skills are a primary channel through which technological change affects wages, employment, and inequality (e.g., Acemoglu and Autor 2011; Acemoglu and Restrepo 2022). Second, occupations consist of (evolving) bundles of cognitive, socioemotional, and manual skills, such that workers at all levels perform a mixed set of tasks (e.g., Arntz et al. 2016; Deming and Kahn 2018; Autor et al. 2024). As such, the composition of skill demand likely mediates how automation affects workers' outcomes (Bennett et al. 2022). Third, the relationship between skills and wages reveals how firms value different capabilities, with posted wages serving as reservation prices that reflect broader labor market dynamics.

Building on this conceptual foundation, the analysis addresses four research questions. First, how does firm demand for skills vary across major occupational groups in the Slovak online labor market, and what systematic distinctions emerge between white-collar and blue-collar occupations? Second, which in-demand skill categories are associated with wage premia or penalties in posted vacancies? Third, how does the conditional demand for specific skill groups vary with firms' degree of automation adoption? Fourth, how is occupational exposure to different types of automation technologies–AI and machine learning, software, and robotics–shaped by the composition of in-demand skills, and which skill types appear to function as a shield against such exposure?

To address these questions, I examine variation in firms' skill demands using a cross-sectional dataset of approximately 350,000 job vacancies posted on Slovakia's largest online job board between January 1 and December 31, 2022. Skill requirements are extracted from unstructured vacancy text using the *ExtractSkills* algorithm developed by Kanders and Sleeman (2021) and classified into fifteen conceptual categories nested within three broader domains: cognitive, socioemotional, and manual skills. This taxonomy follows Bennett et al. (2022) and is operationalized by mapping extracted skills to their closest representations in the high-dimensional semantic space generated by the *JobBERT* model (Zhang et al. 2022). This procedure allows for a systematic assessment of skill demand intensities across occupations - one that is comparable across time and across different samples of online job vacancies.

I find systematic and meaningful variation in skill demand across occupations, reflecting underlying differences in task content and occupational roles. In white-collar roles, demand concentrates on cognitive, socioemotional, software-specific, and managerial skills–non-routine, analytical competencies typically associated with higher education and specialized expertise (Deming and Noray 2020). For instance, advanced skills in machine learning and AI are frequently sought in high-skilled professional roles but remain largely absent in lower-skilled blue-collar jobs. In contrast, blue-collar occupations exhibit strong demand for physical and procedural skills–such as hand––foot–eye coordination, character traits, and finger dexterity–alongside cognitive and interpersonal skills. These roles increasingly require foundational coding and troubleshooting abilities, reflecting the growing integration of automated systems, digital tools, and machinery into blue-collar work environments (Cappelli 2015; Hershbein and Kahn 2018; Handel 2016).

Second, to examine the association between skill demand and earnings, I relate the presence of in-demand skills to advertised wages, controlling for a range of observable vacancy characteristics. The results show that social, cognitive, character, people management, project management, software-specific and technical support, and machine learning and AI skills are all correlationally associated with positive wage premia. Among these, machine learning and AI skills yield the largest premia of 4%, reflecting both their scarcity and high market valuation. These findings are consistent with evidence from other labor markets, including the U.S. (Alekseeva et al. 2021), and the U.K. (Garcia-Lazaro et al. 2025). By contrast, skills such as hand–foot–eye coordination, writing, customer service, physical abilities, and general computer skills are not associated with wage premia and in some cases are linked to wage penalties. Overall, in-demand skills explain approximately 25% of the variation in posted wages, highlighting a strong association between skill requirements and earnings–an empirical pattern extensively documented in previous research.

Lastly, I study whether the conditional number of in-demand skills differs across firms that are more tilted toward the adoption of automation technologies, as proxied by the occupational structure of their labor demand. I also assess whether the composition of in-demand skills is systematically associated with occupations that are more susceptible to automation technologies. Different automation technologies affect distinct types of tasks and skills. One strand of the literature argues that computer-based technologies primarily substitute for routine cognitive tasks while complementing non-routine ones (Autor et al. 2003). Another strand highlights that machinery-type technologies–such as industrial robots or computer numerically controlled (CNC) machines–primarily displace routine manual tasks, while potentially complementing non-routine manual work (Acemoglu and Restrepo 2020; Boustan et al. 2022). More recent advances in AI suggest a nuanced pattern: AI systems may increasingly substitute for non-routine but easy-to-learn tasks (Acemoglu 2024), while tasks that are harder to learn or more complex in structure may exhibit strong complementarities with AI (Brynjolfsson et al. 2025; Acemoglu 2024). Therefore, to study the interplay between technological change and skill demand, the classification of skill groups should be broad and conceptually aligned with the existing literature–a point I elaborate on in later sections.

Whether automation leads to substitution or complementarity has direct implications for labor demand. Task substitution typically reduces employment and wages for affected workers, particularly when productivity gains are limited and workers cannot reallocate to non-automated tasks (Restrepo 2023). In contrast, task complementarity may enhance both employment and earnings. Therefore, the net effect of automation on employment is ambiguous and ultimately remains an empirical question (Arntz et al. 2019).

To measure occupational exposure to automation, I build on the notion that automation innovations have the ability to substitute for labor inputs in production. Using the methods proposed by Autor et al. (2024), I represent occupational descriptions (consisting of bundles of labor tasks) and innovations (represented by patent text) as vectors of semantic representations, effectively capturing the meaning of words and their similarity in vector space - and hence the susceptibility to automation. Exposure scores are computed by summing the number of patents that are highly similar to the task inputs of each occupation–i.e., those that closely match the occupational tasks. To distinguish among types of automation, I adopt a dictionary-based classification inspired by Webb (2019) and Hémous et al. (2025), categorizing technologies into three broad groups of automation technologies: AI and machine learning, software, and robotics.

Using these novel measures, I assess whether firms with higher adoption of automation technologies–proxied by the occupational structure of their labor demand–exhibit lower conditional demand for skills. This approach is analogous to Acemoglu et al. (2022), who infer automation adoption from the labor demand patterns of adopting firms, as reflected in their hiring of workers exposed to automation technologies, including AI and machine learning, software, and robotics. This empirical strategy compares the conditional demand for skills–disaggregated across fifteen conceptual categories–between firms with higher adoption of automation technologies and those with lower adoption, as proxied by the occupational structure of their job postings.

The results reveal that firms more exposed to AI, machine learning, and software technologies tend to correlationally exhibit higher conditional skill demand. In contrast, firms whose occupational structure is tilted toward robotics-exposed roles show lower demand across most of the skill categories, on average. Across all technologies, a hump-shaped relationship emerges, with the highest levels of skill demand across all conceptual categories of skills observed at intermediate levels of automation adoption.

Subsequently, I examine whether the composition of in-demand skills systematically varies with occupations' susceptibility to automation technologies. The results indicate that hand–foot–eye coordination, financial, and machine learning and AI skills are negatively associated with exposure across all technologies, suggesting that these skills may serve as a shield against automation. Software-specific skills, in particular, are linked to lower exposure to robotics, likely reflecting their role in tasks less easily automated by physical machinery. By contrast, language and customer service skills are positively associated with automation exposure. I hypothesize that language skill demand partly reflects the targeting of migrant workers, who were disproportionately placed in routine, automatable roles–suggesting underlying labor market segmentation.

However, these associations may be confounded by reverse causality or omitted variable bias: firms may demand certain skills not to shield against automation, but because those skills are required in occupations already highly exposed to technologies, where they serve as complements. To address this concern, I introduce interaction terms between each in-demand skill and social skills–broadly considered difficult to automate–to help distinguish substitution between skills and machines from potential complementarities. The results indicate that physical, financial, and AI-related skills, when combined with social skills, are positively associated with automation exposure. This suggests that such skill bundles may complement, rather than substitute for, automation technologies.

Nonetheless, the magnitude of the main (substitution) effects generally exceeds that of the interaction (complementarity) effects. Furthermore, the observed hump-shaped pattern in conditional skill demand implies that negative associations between skill demand and automation exposure may partly reflect endogenous technology adoption and within-firm task reallocation, rather than shielding effects alone–a concern I partly address in last identification strategy.

To identify the relationship between in-demand skills and occupational exposure to automation, I apply an inverse probability weighting estimator that reweights observations based on treatment probabilities, conditional on observed vacancy characteristics and firms' decile-level exposure to the other two automation technologies, to control for different automation adoption. This approach approximates a randomized assignment of skill demand. Treatment probabilities are estimated as the likelihood of requiring each skill, conditional on occupation, industry, education, region, and firm-level exposure to unobserved skill substitution patterns.

The resulting average treatment effects reveal a clear divide. Manual and abstract skills–such as physical abilities, hand–eye coordination, software-specific knowledge, people management, and financial competencies–are negatively associated with automation exposure, suggesting that these skills function as a shield against current automation technologies.

These findings align with the framework by Acemoglu and Autor (2011). In contrast, routine skills situated near the middle of the skill distribution–such as finger dexterity, customer service, and cognitive skills in narrow sense–are positively associated with automation exposure across all technologies, indicating that these skills-when required-are in occupations more susceptible to automation. Social and character skills also exhibit positive associations with automation exposure, likely reflecting their complementary role in tasks that co-evolve with new technologies. While these skills are difficult to automate (Bessen 2015; Deming 2017), their presence in highly exposed occupations suggests a form of human–machine complementarity.

Nevertheless, in the absence of exogenous variation in skill demand–such as from a field experiment, natural experiment, or valid instrumental variable–the causal relationship between skill requirements and automation exposure remains underexplored.

This paper relates and contributes to several streams of literature. First, it builds on and contributes to the literature that examines the skills-earnings association in the labor market (Deming and Kahn 2018; Hanushek et al. 2015; Hershbein and Kahn 2018; Deming and Noray 2020). In the context of technological change, the skills-earnings association prove immensely robust in a variety of dimensions when looking at labor market earnings. For example, Hanushek et al. (2015), using PIAAC and other earnings data, find that cognitive skills measured across numeracy, literacy, and problem-solving domains are systematically associated with higher wages, with the highest value a few years after workers enter the labor market. A larger strand of the literature prefers to use online job vacancies to study the heterogeneity of labor demand and the value of skills. Deming and Kahn (2018) investigate the central role of cognitive and social skills in predicting occupational wage differentials across local labor markets. Their results suggest that the variation across firms in worker pay and firm performance is indeed related to the demand for these two skill categories. These effects are more pronounced in routine-cognitive occupations, which also have relatively the highest wage growth (Hershbein and Kahn 2018). Deming and Noray (2020) find that the earnings premium for college graduates majoring in STEM fields is highest at labor market entry, but declines rapidly, pushing these graduates out of technology-intensive fields as they gain experience. With the advent of AI, Alekseeva et al. (2021) were the first to show that the demand for AI skills has increased dramatically over the past decade across most industries and occupations. They also found that if AI-related skills are in-demand, such vacancies offer a significant wage premium, and firms will exhibit above-average wages and productivity. By examining heterogeneity in online skill demand similar to Deming and Kahn (2018) and examining its association with earnings, this paper aims to expand on this approach. This expansion includes the inclusion of a comprehensive category of manual skills, as well as machine learning and AI skills, building upon the taxonomy of Bennett et al. (2022). In addition, this paper directly extends Bennett et al. (2022)s' work by estimating the skill premium or penalty associated with their conceptual skill categories. Despite extending the cross-sectional dimension of skills, I have only a single snapshot in time of online job vacancies. However, changes in skill demand over time and within occupations remain unexplored.

Second, this paper is linked to the literature exploring the susceptibility of automation (Webb 2019; Frey and Osborne 2015; Felten et al. 2021; Brynjolfsson et al. 2018; Autor et al. 2024; Engberg et al. 2024). This paper builds on the notion that automation innovations can substitute for labor in production. Using the method proposed by Autor et al. (2024), I construct the first Europe-specific measures of occupational exposure to automation. To capture heterogeneity across technologies, I extend their approach by adopting a dictionary-based classification inspired by Webb (2019) and Hémous et al. (2025), distinguishing between AI, machine learning, software, and robotics. By examining technological change and automation exposure in a European context, the paper contributes new regional evidence to a literature that has thus far focused predominantly on the U.S.

Third, it aligns with and contributes to the emerging literature on the labor market effects of technologies such as AI and machine learning. By analyzing online job vacancies, it examines how these technologies influence labor demand and the wage premia associated with AI and machine learning-related skills (Acemoglu et al. 2022; Alekseeva et al. 2021; Garcia-Lazaro et al. 2025).

Finally, but in a minor sense, this paper also contributes to the literature examining the demand for skills in the online labor market and their systematic co-occurrence across differentiated occupations (Boselli et al. 2017; Bennett et al. 2022; Beblavý et al. 2016; Grinis 2019; Squicciarini and Nachtigall 2021; Fabo and Kahanec 2020). In addition, this paper is connected to the research conducted by Štefánik et al. (2023) and Košt'álová et al. (2022), which also utilize the same online job vacancy data to analyze the Slovak labor market. Štefánik et al. (2023) show that online job vacancies are a significant predictor of official vacancy statistics, unemployment, and employment in the Slovak labor market. Košt'álová et al. (2022) assess which observable vacancy characteristics increase or decrease the number of user views of individual online job vacancies.

However, due to data constraints, this paper remains agnostic about the strand of literature focusing on the dynamic nature of skills within occupations over time, despite the significant impact of such changes (Atalay et al. 2018; Bessen 2015). It also does not address the supply side of the labor market (Balgova et al. 2023) or the broader range of firm-level characteristics that influence labor demand and earnings (Alekseeva et al. 2021).

2 Data and methods

This section outlines the procedure for extracting skills from unstructured online job vacancy data and mapping them into a structured taxonomy of conceptual skill categories. I then describe the construction of an occupational exposure measure to automation technologies, based on semantic similarity between patent texts and occupational task descriptions.

Finally, I present the empirical strategy, which involves estimating skill premia in the online labor market, analyzing how conditional skill demand varies with firm-level automation exposure–proxied by the occupational structure of labor demand–and assessing whether specific skill groups are associated with lower exposure, thereby identifying skills that may serve as a shield against automation.

2.1 Online job vacancies data

My primary data source is a database of online job vacancies predominantly available in Slovak, accessible via the website https://www.profesia.sk. First, I transl ated the extracted descriptions of online job vacancies into English using Google Translate. Online job vacancies published in languages other than Slovak were not excluded, as the application programming interface (API) is designed to automatically detect the source language during translation. In order to verify the reliability and accuracy translation tool works, I undertook three consecutive steps. First, I randomly selected 1,200 online job vacancies and translated them using the ChatGPT 3.5 Turbo model[1] Next, I utilized the *JobBERT* large language model developed by Zhang et al. (2022) to obtain dense vectors of sentence embeddings. Lastly, I computed the cosine similarities between the Google translation and the ChatGPT translation, plotting the histogram of the obtained cosine similarities in Fig. 4 in the Appendix. The graph is heavily left-skewed and close to one. The mean cosine similarity between translations is 0.975, indicating a high degree of similarity between the two translation outputs, while the standard deviation is 0.035, suggesting minimal variation in similarity across the translations, which reassures us of the reliability of the translation used.

The dataset comprises approximately 350,000 online job vacancies posted between January 1 and December 31, 2022, by roughly 21,000 distinct firms. Profesia's platform adjusts for reposting behavior, ensuring that each vacancy is recorded only once.

Alongside the unstructured text on tasks and prerequisites from online vacancies, the dataset also contains structured metadata extracted by the original compilers of the database. The metadata contains 4-digit ISCO-08 occupational codes and 2-digit industry codes based on Profesia's internal classification system. It also contains information on minimum and maximum educational requirements, region of work, offered benefits, and the posted monthly wage (including wage ranges when available). Additional variables include contract type (i.e., full-time or part-time), work modality (on-site, online, or hybrid), and whether the vacancy was posted directly by an firm or via a recruitment agency.

Industry labels in the dataset are self-reported by employers, resulting in substantial duplication and lack of standardization–yielding approximately 14,000 unique entries. To reduce this complexity, I infer a primary industry for each firm by assigning the modal label across its job postings. If no mode exists (i.e., all entries are unique), the firm is classified under a separate 'ambiguous industry' category. This procedure reduces the number of unique industry values to roughly 3,000, hereafter referred to as industries.

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[1] I set the temperature of the model to 0 to ensure maximum accuracy, minimizing the model's creativity. The API call used the following prompt: 'Translate the following to English: {text}'.

To enable sector-level analysis, I further aggregate these industry labels into a broad sectors aligned with the NACE Rev. 2 classification presented in Table 5. First, I translate all firm-reported labels into English using Google Translate. I then use ChatGPT−3.5 Turbo[2] to classify each translated label into one of the 21 NACE Rev. 2 sectors (A-U). Prompts explicitly instruct the model to return a single letter. If the response contains multiple letters, I retain only the first, hereafter referred to as sectors. This method performs well, particularly for lengthy or ambiguous labels, as confirmed by manual inspection.

The resulting broad sector categories serve as the basis for estimating both the skill–earnings association (Eq. (3)) and automation exposure conditional on composition of in-demand skills (Eqs. (5) and (6)) across sectors.

Hereafter, wages refer to those advertised in job vacancies, not realized earnings from administrative data or self-reported surveys. I use posted wages to estimate the premia or penalties associated with specific skill requirements. Although posted wages do not necessarily reflect the eventual negotiated wage, they proxy firms' reservation demand price–the minimum compensation employers are prepared to offer for specific skills. Hereafter, I assume that workers' bargaining power is fixed–potentially at zero, but at least constant along the relevant margin. Moreover, subsequent estimates may diverge from realized wages, which are shaped by worker–firm matching and unobserved labor supply and demand dynamics.

In Slovakia, wage information is especially prevalent in job postings, with approximately 95% of online job vacancies including wage data due to a legal mandate introduced in May 2018 (Law No. 63/2018 Collection of Laws), which amended the Slovak Republic's Labor Code (Law No. 311/2001 Collection of Laws). This requirement compels employers to disclose wage information in job listings, resulting in a more comprehensive dataset for analyzing wage trends in Slovakia. This stands in contrast to countries such as the U.S., where only about 14% of job postings include wage information (Batra et al. 2023).

When assessing wages and skill demand, online job vacancy data offer two significant advantages over traditional sources such as labor force surveys: granularity and detail (Fabo and Kureková 2022). However, these data are not inherently representative, and certain occupations are disproportionately represented compared to the actual labor force, as captured in representative surveys or administrative data covering all workers. In fact, online job vacancies do not reflect the true structure and size of labor demand in the economy.

Figure 6 illustrates that specific occupations–such as professionals and technicians and associate professionals–are substantially overrepresented in the online vacancy data, with two to three times as many postings relative to their proportional share in the labor force. These groups alone account for over 70% of all online vacancies in the dataset. By contrast, service and sales workers, crafts and related trades, plant and machine operators, and elementary occupations are markedly underrepresented. Despite their low employment shares, managers and skilled agricultural, forestry, and fishing workers are proportionally represented in the postings. This imbalance could potentially inflate estimated skill premiums for in-demand capabilities such as digital or managerial skills. Although I do not have direct evidence of this effect, the concern is consistent with findings from Adrian and Lydon (2019), who report that wage patterns in online postings broadly align with those observed in EU-SILC income data. Nevertheless, the results should be interpreted as reflecting skill demand within the online labor market rather than a representative labor force survey. To partly account for this bias, all models introduced in Eqs. (3), (5) and (6) include both unweighted and weighted regressions, using weights based on the relative employment shares of major occupational groups sourced from EU-LFS.

Another limitation of online vacancy data is that they may not fully capture the extent of technology adoption. Firms often acquire skill expertise through internal training or by purchasing products or services in external markets, neither of which would be reflected in job advertisements (Alekseeva et al. 2021).

While Profesia's dataset offers useful insights, it does not fully capture true skill demand or the pace of technology adoption in Slovakia. Accordingly, results for occupations and industries dominated by lower-skilled workers should be interpreted with caution. In particular, roles such as plant and machine operators and assemblers–and their associated skill profiles and wage levels–may be underrepresented or entirely absent, since this segment is the least represented in the data.

2.2 Skills extraction

Online job vacancies typically consist of raw, unstructured text, making the skill extraction a complex and non-trivial task. A growing body of research has developed algorithms and pre-trained language models to address this challenge, offering valuable tools for extracting structured information from vacancy text. In what follows, I outline the principal methods and approaches employed to achieve the paper's first objective: extracting and classifying skills into conceptual categories. Figure 1 illustrates the skill extraction process and its mapping to the conceptual skill taxonomy.

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[2] Again, to ensure deterministic outputs, the temperature parameter is set to 0.0.

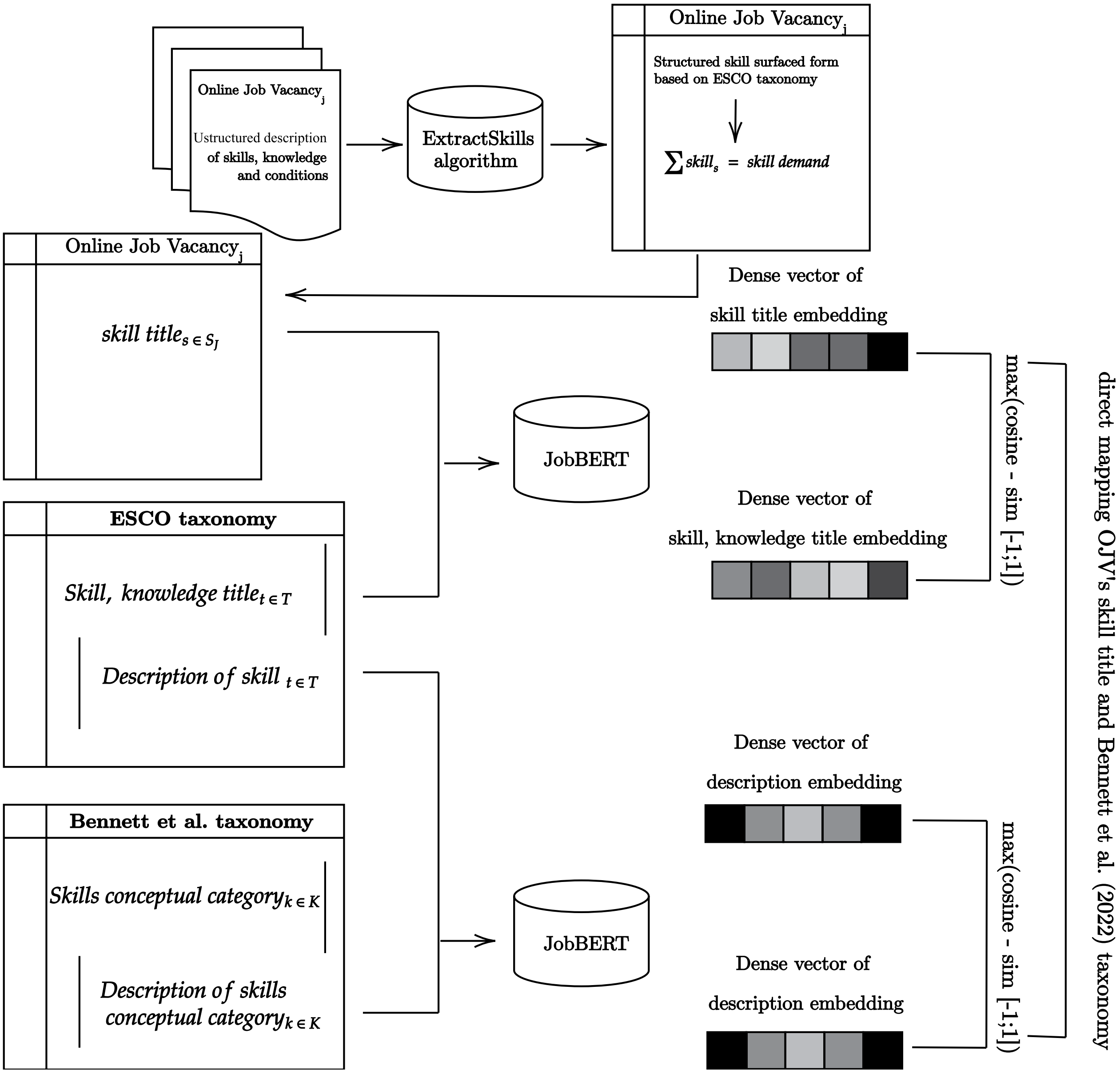

Fig. 1 Schematic representation of skills extraction from online job vacancies and their mapping to Bennett et al. (2022)'s conceptual skill taxonomy

First, I extract skill demand from unstructured job vacancy text using the *ExtractSkills* algorithm developed by Kanders and Sleeman (2021). *ExtractSkills* generates surface forms–simplified textual variants of ESCO skills–through preprocessing (i.e., lemmatization, stopword removal), noun phrase extraction, and manual refinement, aiming to broaden the set of potential matches as much as possible. For example, the ESCO skill 'handle helpdesk problems' yields forms such as 'helpdesk' and 'helpdesk problem'. This process produces approximately 130,000 surface forms–an average of 10 per skill–which are then matched to job vacancies. To reduce false positives, matches are filtered using term frequency-inverse document frequency scores that assess the contextual relevance of each match. This approach provides a robust method for large-scale skill extraction from job vacancies (Kanders and Sleeman 2021).

Applying this method, I construct a vector of approximately 330,000 non-empty skill entries–comprising nearly 2,000,000 non-unique mentions–extracted from online job vacancies. While anchored in ESCO, these surface forms do not always exactly match canonical titles, reflecting the nuanced and context-dependent nature of skill expression. To improve the precision of mappings between extracted titles in a surface form and ESCO skill titles, I complement the rule-based approach with the *JobBERT* model, which estimates contextual similarity between extracted titles in their surface form and ESCO skill titles.[3]

To formalize this process, let J denote the set of job vacancies, and let S_J be the set of extracted surface-form skill titles. Let T be the set of all ESCO-defined skills and knowledge concepts, and let V the shared embedding space.

The first mapping procedure is defined as follows:

I. Embed each extracted skill title in a surface form $s \in S_J$: $S_J \to \{\text{Embed}(s) \mid s \in S_J\}$
II. Embed each ESCO skill title $t \in T$: $T \to \{\text{Embed}(t) \mid t \in T\}$
III. For each $s \in S_J$, assign the ESCO skill title $t^* \in T$ that maximizes cosine similarity in V

To study how skill demand relates to technological change, I draw on a conceptual taxonomy synthesized by Bennett et al. (2022), which is grounded in a parsimonious body of economic literature that classifies skills along dimensions relevant to technology exposure and task automation (e.g., Autor et al. 2003; Deming and Kahn 2018; Hershbein and Kahn 2018; Heckman and Kautz 2012). This taxonomy offers a structured and theory-informed framework for capturing the economic significance of different skill types–particularly in the context of automation–making it well-suited for empirical objectives of this paper.

The next step involves classifying each ESCO skill into one of the conceptual categories outlined in Table 3, which summarizes the skill categories and their corresponding textual descriptions used as reference definitions. This classification is implemented as a semi-supervised task, based on the semantic similarity between ESCO skill descriptions and the description of each conceptual category.

The second mapping procedure is defined analogously as follows:

I. Embed the ESCO descriptions $t \in T$: $T \to \{\text{Embed}(t) \mid t \in T\}$
II. Embed the skill category descriptions $k \in K$ from the conceptual taxonomy of Bennett et al. (2022): $K \to \{\text{Embed}(k) \mid k \in K\}$
III. For each $t \in T$, assign the category $k^* \in K$ that maximizes cosine similarity in V

This two-stage pipeline yields a mapping from job-level extracted skills to standardized ESCO concepts, and from those concepts to high-level skill categories that are analytically meaningful for research on automation and technological change.

Table 2 illustrates this process using two contrasting occupations. The top panel shows 23 skills extracted from a white-collar vacancy, and the bottom panel shows 4 from a blue-collar vacancy. Skills are listed in their ESCO surface form (left column) and mapped to conceptual skill categories using the semantic similarity of their descriptions (right column).

While effective overall, the method is not without minor inaccuracies. For example, the algorithm occasionally retrieves false positives such as the ESCO skill 'installing structural masonry materials', which did not appear in the original job text. Such cases are rare but underscore the need for cautious interpretation. Nonetheless, the vast majority of extracted and classified skills accurately reflect actual demand as expressed in online job vacancies.

2.3 Exposure to automation

My subsequent objective is to measure the exposure of European occupations to innovations that have the potential to substitute for workers' task inputs. Following the methodology proposed by Autor et al. (2024), I represent occupational descriptions–comprised of bundles of labor tasks–and innovations–captured through patent text–as dense semantic vectors. This embedding approach maps both types of text into a shared high-dimensional vector space, enabling the measurement of similarity in meaning and, by extension, the susceptibility of occupations to automation.

I proxy technological progress using patent data, focusing on granted patents published between 1980 and 2020, sourced from the Google Patents Public Dataset. To distinguish among types of automation, I adopt a dictionary-based classification strategy inspired by Webb (2019) and Hémous et al. (2025), categorizing patents into three broad classes of automation-related technologies: AI and machine learning, software, and robotics. I construct quasi-labeled subsamples of patents that contain predefined keywords in either the title or abstract. Specifically, a patent is classified into one or more categories based on the presence of relevant keywords.[4] To maximize coverage, I include all worldwide patents with English-language titles and abstracts, yielding a dataset of

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[3] *JobBERT* is fine-tuned on a large corpus of job vacancy titles paired with skill sets. The model is trained via distant supervision using ESCO, allowing it to learn embeddings that capture real-world co-occurrence patterns between occupations and skills Zhang et al. (2022). This enables scalable, unsupervised classification by embedding both surface forms and ESCO concepts in a shared high-dimensional semantic space. The model is publicly available at: https://huggingface.co/jjzha/jobbert_skill_extraction.

[4] A patent is included in a given category if its title or abstract contains at least one of the following keywords: *Robotics:* robot*, mechatroni(c|cs), cyber-physical, system, computer vision, control systems, sensor; *Software:* software, algorithm, computer program, data structure; *AI and machine learning:* artificial intelligence, machine learning, neural network, deep learning.

approximately 2.4 million unique patents. Although overlap across categories is possible, each subsample captures a qualitatively distinct technological domain.

To represent occupational task inputs–that is, the specific work activities that may be automated–I rely on detailed textual task descriptions for 427 ISCO-08 unit-level occupations, compiled and cleaned by Mihaylov and Tijdens (2019).[5]

To embed both patent and task texts into a shared semantic space, I use the BERT-for-Patents model developed by Srebrovic and Yonamine (2020), which has been fine-tuned on the full corpus of Google Patents.[6] This transformer-based model incorporates an attention mechanism that captures contextual meaning more effectively than earlier models such as GloVe, particularly in the presence of linguistic ambiguity or polysemy. Unlike Autor (2022), who use TF-IDF–weighted GloVe embeddings, I adopt a contextualized language model that requires no additional preprocessing (e.g., lemmatization or stop-word removal), aside from minimal filtering to eliminate unsystematic noise in the patent abstracts.

Having obtained dense vector representations of occupational tasks and patent documents, I construct a matrix $X^{\tau}_{p,j}$ of cosine similarities between patent p and the task content of occupation *j*, specific to automation technology τ. The parameter $\tau \in \{\text{AI and machine learning, software, robotics}\}$ denotes the quasi-labeled technology category assigned to each patent. Following Autor et al. (2024), I retain the top 15% of cosine similarity scores across all patent–occupation pairs (*p*, *j*) by applying the following thresholding rule:

$$I^{\tau}_{p,j} = 1 \text{ if } X^{\tau}_{p,j} \geq \lambda^{\tau} \text{ and zero otherwise;} \tag{1}$$

where λ^{τ} is a threshold based on the similarity distribution for technology τ across period the $t \in \{1980, 2020\}$ across all occupations. Let P^{τ} represent the set of patents classified based on technologies τ, and let *J* represent the set of all occupations. In the final step, I aggregate the most similar patents that are likely to substitute the occupational tasks within each set of technology in the following way over the entire period *t* to obtain the cumulative exposure to automation Aut^{τ}_{j} of occupation *j*:

$$\text{Aut}^{\tau}_{j} = \sum_{p \in P^{\tau}} \sum_{j \in J} I^{\tau}_{p,j} \tag{2}$$

Since Aut^{τ}_{j} is a count variable, I transformed the counts using the inverse hyperbolic sine (IHS) transform.

Figure 2 provides a schematic illustration of the workflow used to measure occupational exposure to automation technologies.

2.4 Empirical strategy

With the consolidated skill demand, offered wages, and newly constructed measures of occupational exposure to automation technologies in hand, I am now equipped to empirically address the core research questions. The empirical strategy proceeds in three steps. First, I estimate the association between skill demand and offered wages, providing evidence on the initial labor market valuation of different skill categories. Second, I examine how conditional skill demand varies with firm-level adoption of automation technologies, capturing potential demand shifts driven by technological substitution. Third, I investigate whether the presence of specific skill groups in job postings is associated with lower exposure to automation

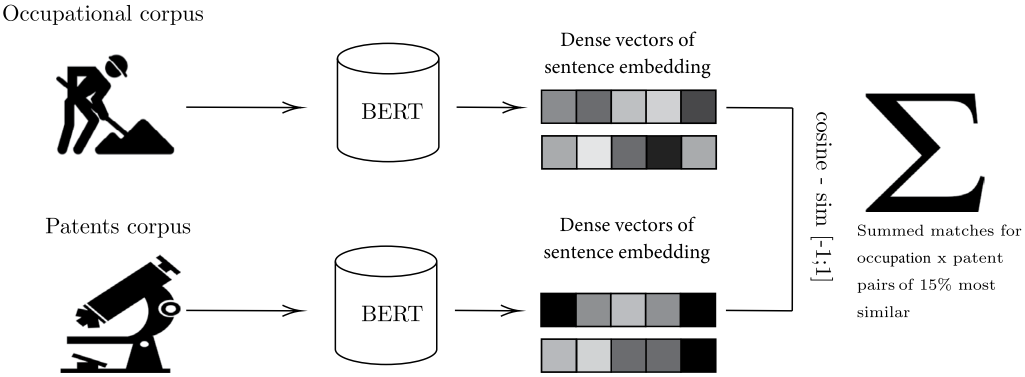

Fig. 2 Schematic representation of constructing automation exposure measures inspired by Autor et al. (2024)

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[5] For example, tasks associated with a Weaving and Knitting Machine Operator include: 'Setting up and operating batteries of automatic, link-type knitting machines to knit garments of specified pattern and design' and 'Threading yarn, thread and fabric through guides, needles and rollers of machines for weaving, knitting or other processing.' In contrast, tasks for an Electrical Engineer include: 'Advising on and designing power stations and systems which generate, transmit and distribute electrical power' and 'Supervising, controlling and monitoring the operation of electrical generation, transmission and distribution systems.'

[6] The model is publicly available at: https://huggingface.co/anferico/bert-for-patents.

technologies–thereby identifying which skills may serve as a shield against automation.

2.4.1 Estimating skills-earnings association

First, to study relationship between in-demand skills and offered wages in the online job vacancies, I estimate the following regression:

$$\log(\omega_{ojv,j}) = \beta_0 + \beta_{k\in K}\mathrm{v} + \delta_o + \gamma_i + \omega_t + \varepsilon_{ojv,j} \quad (3)$$

where ω_{ojv} represents monthly wage in online job vacancy *j*, v is a $1 \times K$ features vector, where K is the total number of conceptual skill categories. Each element of v represents counts of skills in each *ojv* across all categories $k \in K$ capturing the individual intensity of skill demand for each category as in the previous literature (Deming and Kahn 2018). A positive β_k coefficient would imply a skill premia, while a negative β_k would indicate a skill penalty offered by an online labor demand. In this model, a skill premia is defined as the additional wage return associated with demand for a specific conceptual skill category in online job vacancy, holding all other characteristics constant. Parameter δ_o denotes the fixed effect for each broader occupational group *o* defined at the 1-digit level, γ_i denotes the industry fixed effect, ω_t is the month fixed effect, and $\varepsilon_{ojv,j}$ represents the error term. In the fully specified model, I add to the Eq. (3) a vector $\mathbf{Z_j}$ of control variables capturing region of work, workplace type, temporary work agencies, type of contract and minimal education level at the online job vacancy level.

As a robustness check, I re-estimate the main specification separately across four broad sectors–primary, secondary, private services, and public services–using the aggregated industry classification outlined in Table 5.

2.4.2 Estimating skill demand conditional on firm-level adoption of automation technologies

Second, I investigate whether firms with higher adoption of automation technologies–proxied by the occupational structure of their labor demand–exhibit lower conditional demand for skills. This approach parallels Acemoglu et al. (2022), who infer automation adoption from the labor demand patterns of adopting firms–specifically through their hiring into occupations that are exposed to automation technologies, including AI and machine learning, software, and robotics. The hypothesis is motivated by their empirical finding that firms whose labor demand is more tilted toward automation-exposed occupations–i.e., those observably adopting automation technologies–tend to reduce the skill intensity of their job postings over time, suggesting potential substitution. While their study is based on a panel structure, I examine this relationship in a cross-sectional framework. Specifically, this empirical strategy compares the conditional demand for skills between 21,000 distinct firms with higher versus lower adoption of automation technologies, proxied by the average automation exposure based on the occupational structure of their job postings.

To estimate the conditional mean demand for different types of skills, disaggregated by conceptual skill category (skill group), I estimate the following model:

$$\text{Skill group}^k_{ojv,j} = \beta_0 + \beta_1\mathcal{F}^\tau_f + c\mathbf{Z_j} + \delta_o + \gamma_i + \omega_t + \varepsilon_{ojv,j} \quad (4)$$

In Eq. (4), the dependent variable $\text{Skill group}^k_{ojv,j}$ denotes the number of skills from group *k* listed in vacancy *j*. To compare conditional skill demand across fifteen conceptual categories between firms with higher versus lower adoption of a given automation technology τ, I construct a binary indicator, $\mathcal{F}^\tau_f$, which equals 1 if firm *f* lies above the 70th percentile of the distribution of average labor demand exposure to technology $\tau \in \{\text{AI and machine learning, software, robots}\}$, and 0 otherwise.

The coefficient β_1 captures the difference in conditional mean skill demand for group *k* between firms with high adoption of automation technologies and the rest of the sample.

A negative β_1 implies that firms closer to the frontier of adoption for a given technology demand fewer skills in group *k* relative to less-exposed firms. Conversely, a positive β_1 suggests that high-exposure firms demand more of these skills.

The specification includes a vector of control variables $\mathbf{Z_j}$ at the vacancy level, capturing region of work, workplace type, temporary agency status, contract type, and minimum required education. Fixed effects δ_o, γ_i, and ω_t control for occupation (at the 1-digit ISCO level), industry, and calendar month, respectively. The term $\varepsilon_{ojv,j}$ denotes the error.

To explore a potential hump-shaped relationship between firms' exposure to automation technologies and skill demand, I estimate the model in Eq. (4) for firms above the 50th and 90th percentiles of the distribution of mean labor demand exposure across the full sample, for technology τ.

Subsequently, I estimate the unconditional mean skill demand for each group *k* across the percentiles of firms' labor demand exposure.

2.4.3 Estimating automation exposure conditional on composition of in-demand skills

Third, to assess whether the presence of a specific skill group in job postings is associated with lower exposure to automation technologies–and thereby identify which skills may serve as a shield against automation–I estimate the following regression specification:

$$\mathrm{Aut}^{\tau}_{ojv,j} = \beta_0 + \beta^{\tau}_{k\in K}\mathrm{v} + \delta_o + \gamma_i + \omega_t + \varepsilon_{ojv,j} \quad (5)$$

where $\mathrm{Aut}^{\tau}_{ojv,j}$ denotes the standardized exposure to automation technology $\tau \in \{\text{AI and machine learning, software, robots}\}$ for ISCO-08 occupation *j* at the unit group level. The exposure measures are standardized prior to merging with the vacancy-level data, such that the distribution of automation exposure across all 427 ISCO-08 occupations has mean zero and standard deviation one, separately for each technology τ. The features vector v consists of elements corresponding to counts of skills $k \in K$ conceptual skill categories. The parameters δ_o, γ_i, and ω_t again represent fixed effects for broader occupational groups, industries, and months, respectively. In the fully saturated model, I also include a vector $\mathbf{Z_j}$ of control variables capturing job vacancy characteristics such as region of work, workplace type, temporary work agency involvement, contract type, and minimum education level.

On the one hand, a positive estimate of $\beta^{\tau}_{k\in K}$ in Eq. (5) does not necessarily imply that certain skills are driving increased exposure to automation. It is possible that these skills are in demand precisely because occupations with a high presence of automation technologies still require them–i.e., automation may not yet be capable of performing certain essential tasks, leading firms to continue hiring for those skills.

To partly address this concern, I build on the argument by Deming (2017) that computers (machines) excel at executing routine and codifiable tasks but struggle with tasks requiring interpersonal interaction. As a result, non-routine interpersonal work–i.e., social skills–becomes increasingly valuable as technology substitutes for routine labor. To further distinguish between skill–machine complementarity and substitutability, in line with the framework of Acemoglu and Autor (2011), I introduce interaction terms between each in-demand skill $k \in K$ (excluding social skills) and social skills, which are inherently difficult to automate *per se*. Specifically, I estimate the following regression model:

$$\mathrm{Aut}^{\tau}_{ojv,j} = \beta_0 + \beta^{\tau}_{k\in K}\mathrm{v} + \gamma^{\tau}_{k\in K}\left(\mathrm{v}\cdot \text{Social Skills}\right) + c\mathbf{Z_j} + \delta_o + \gamma_i + \omega_t + \varepsilon_{ojv,j} \quad (6)$$

This specification aims to capture the dual nature of skill demand in relation to automation exposure. A negative main effect $\beta^{\tau} k \in K$ indicates that a higher count of skills in category *k* is associated with lower occupational exposure to automation–suggesting that these skills act as a shield against automation by making occupations less susceptible to technological substitution. In contrast, a positive interaction effect $\gamma^{\tau} k \in K$–between skill *k* and social skills–signals potential skill–machine complementarity. This would suggest that when a specific skill set is demanded alongside social skills (which are inherently difficult to automate), it may reflect the use of automation technologies in a complementary rather than substitutive role.

Such complementarities are likely to emerge in occupations where automation technologies are already adopted, not to replace workers, but to enhance their productivity in tasks where human capabilities–especially in social and interpersonal skills–remain essential.

As in previous specifications, the model includes fixed effects for occupations, industries, and months. I also control for vacancy-level characteristics through the vector $\mathbf{Z_j}$, which includes region of work, workplace type, temporary agency status, contract type, and minimum education requirements.

On the other hand, a negative estimates of $\beta^{\tau}_{k\in K}$ in Eq. (5), may not necessarily imply that the associated skills offer shield against automation. Instead, they could reflect a lower levels of automation in certain job contexts, particularly if the relationship between skill demand and firms' adoption of automation technologies is non-monotonic or hump-shaped.

These empirical specifications leverage variation within broader occupational groups while controlling for shared characteristics between these categories, such as typical skill sets, average wage levels, job stability, and training or certification requirements across more broadly defined occupational codes. The industry fixed effects are designed to absorb shocks stemming from trade dynamics and or shifts consumer demand.

To identify the relationship between in-demand skills and automation exposure, I apply an inverse probability weighting (IPW) estimator. This approach reweights observations based on the predicted probability that a vacancy requires a given skill, conditional on occupation, sector, education, region, and the decile of a proxy for firm-level automation adoption, inferred from the occupational structure of desired hirings. A flexible logit model is used to estimate treatment probabilities to balance covariates between treated vacancies (those requiring the skill) and control groups.

For each automation outcome $\tau \in \{\text{AI and machine learning, software, robots}\}$, I estimate the average treatment effect (ATE) of requiring skill *k* as:

$$\mathrm{ATE}^{\tau}_{k} = \mathbb{E}[Y^{\tau}_{j}(1) - Y^{\tau}_{j}(0)] \quad (7)$$

where Y^{τ}_{j} denotes the standardized automation exposure of vacancy *j*, and $D^{k}_{j} = 1$ if vacancy *j* requires skill *k*. Using a binary skill indicator avoids strong assumptions about functional forms and improves interpretability, allowing for a clear comparison between vacancies that do and do not require each skill, conditional on observed characteristics.

Treatment probabilities are estimated using:

$$\Pr(D_j^k = 1 \mid X_j) = \frac{\exp(X_j\beta)}{1+\exp(X_j\beta)},$$

with weights constructed as:

$$w_j = \frac{D_j^k}{\hat{p}_j} + \frac{1-D_j^k}{1-\hat{p}_j},$$

where X_j includes broad occupation, sector, required education, and region. These weights rebalance the covariate distribution across treated and untreated groups. Under the assumptions of conditional unconfoundedness, common support, and the requirement that the treatment of one unit does not affect the outcomes of another (SUTVA), the resulting estimates can be interpreted causally (Rosenbaum and Rubin 1983; Wooldridge 2002; Pearl 2009).

To control for firm-level heterogeneity in skill demand, I additionally condition on deciles of labor demand exposure to the two *other* technologies, τ' and τ'', where $\tau' \neq \tau'' \neq \tau$. This addresses potential bias due to bad controls; $\mathrm{Decile}(Aut_j^{\tau})$, which is constructed from the outcome variable itself, is excluded to avoid conditioning on a descendant of a collider (Cinelli et al. 2024; Pearl 2009). Given the strong correlation across exposure measures, including $\mathrm{Decile}(Aut_j^{\tau'})$ and $\mathrm{Decile}(Aut_j^{\tau''})$ effectively captures unobserved variation in firms' automation adoption and the associated skills-substitution patterns, consistent with Acemoglu et al. (2022) and the discussion in Sect. 2.4.2. Figure 3 illustrates the treatment assignment logic.

As a robustness check, I re-estimate ATE_k^{τ} from the treatment assignment model in Eq. (7), including a decile indicator for offered log wages as an additional matching variable. This adjustment accounts for potential unobserved worker sorting into more productive firms based on their abilities, as documented by Borovičková and Shimer (2017) and Lochner and Schulz (2024).

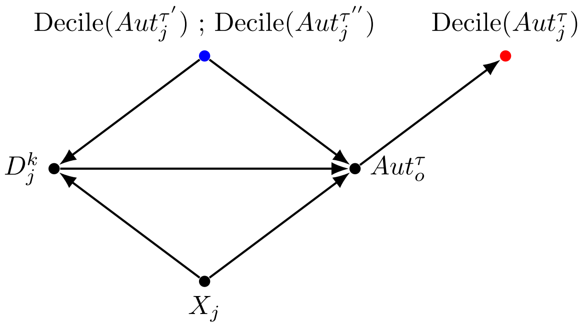

Fig. 3 Directed acyclic graph of the treatment assignment in the identification strategy underlying Eq. 7. The model controls for vacancy characteristics X_j and decile-level exposure to alternative automation technologies–$\mathrm{Decile}(Aut_o^{\tau'})$ and $\mathrm{Decile}(Aut_o^{\tau''})$–while excluding $\mathrm{Decile}(Aut_o^{\tau})$

Despite the popularity of IPW, its performance can be poor due to the instability of the estimated weights. The IPW estimator does not guarantee stable inverse weights, as even small changes in the estimated regression coefficients can lead to large variations in weights–particularly for treated online job vacancies that have a low predicted probability of treatment (Glynn and Quinn 2010). Therefore, as an additional robustness check, I re-estimate the ATEs using the Augmented Inverse Probability Weighting (AIPW) estimator, which improves weight stability. The AIPW method is often referred to as 'doubly robust' because it yields consistent estimates as long as either the treatment assignment model or the outcome model is correctly specified (Kurz 2022).

All models in Eqs. (3)–(4) are estimated using Correia (2016) `reghdfe` estimator. Correia (2016)'s estimator for linear models with multi-way fixed effects leverages graph theory to improve computational efficiency when dealing with high-dimensional fixed effects in large datasets. Traditional methods that rely on dummy variables or within transformations are computationally restrictive with large or multiple fixed-effect categories, often requiring substantial memory and processing time. Correia (2016)'s approach, which treats multi-way fixed effects as a linear system on a weighted graph, allows the use of nearly-linear time estimators from spectral graph theory. This method reduces computational load and memory demands, making it particularly suitable for high-dimensional fixed-effect datasets. Standard errors are clustered at the level of broader occupational groups and industries–unless stated otherwise in the subsector analysis or in the estimation of average treatment effects (as discussed below)–following the recommendations of Abadie et al. (2023). This approach accounts for within-cluster error correlation that may arise from shared shocks or structural conditions within the same occupation or industry. By clustering at this level, I aim to obtain more accurate standard error estimates and avoid the underestimation of variances and inflated significance levels in the reported results.

ATEs are estimated using the `teffects ipw` or `teffects aipw` estimators as developed by Cattaneo (2010); Cattaneo et al. (2013). Observations violating the overlap assumption are identified in a first-stage estimation and excluded,[7] after which models are re-estimated on the restricted sample. The resulting coefficients β_k^{τ} reflect the causal effect of requiring skill *k* on exposure to automation technology τ, under the standard assumption

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[7] Violators account for less than 0.1% of the sample.

of conditional unconfoundedness, SUTVA and common support.

Nevertheless, due to the absence of exogenous variation in skill demand–such as from a field experiment, natural experiment, or instrumental variable–the true causal relationship cannot be fully established.

3 Results and discussion

The empirical analysis proceeds in four main steps, detailed below. First, I present descriptive evidence on extracted skills–both in their raw form and after classification into conceptual categories–across major ISCO occupational groups, using online job vacancy data from Profesia. Second, I examine how specific skill categories relate to wage premia or penalties within broader occupational and industry groups, controlling for key vacancy and firm characteristics. Third, I assess whether firms with higher adoption of automation technologies–proxied by the average exposure implied by their occupational labor-demand structure–exhibit lower conditional demand for skills. Finally, I investigate whether the presence of specific skill groups in job postings is associated with lower exposure to automation technologies, thereby identifying which skills may serve as a shield against automation.

3.1 Descriptive analysis of skill demand in the online labor market

As a starting point, I examine how in-demand skills are distributed across major occupational groups. This allows me to characterize the structure of skill demand in the Slovak labor market, using 2022 job vacancy data from the country's largest online job board. I extract nearly two million non-unique skills from raw text descriptions and classify them into fifteen conceptual categories introduced in Sect. 2.2. Vacancies list, on average, almost six skills–somewhat fewer than the nine observed in Deming and Noray (2018), which focused solely on STEM jobs.[8]

Second, I examine how skills are distributed across major ISCO occupational groups. I describe these groups as follows: *white-collar high-skilled* (including managers, professionals, technicians and associate professionals), *white-collar low-skilled* (including clerks, service, and sales workers), *blue-collar high-skilled* (including skilled agricultural and fishery workers, craft and related trades workers), and *blue-collar low-skilled* (including plant and machine operators, assemblers, and elementary occupations). As a first step, I analyze the distribution of the most in-demand skills within occupational groups.

Following standard NLP practice, I pre-process the extracted skills in their raw, non-contextualized form by removing stopwords and applying lemmatization. To capture not only the distribution of individual words in the extracted skills but also their combinations, I construct bigrams (pairs of consecutive words)[9] and visualize them in word clouds for each major occupational group in Figs. 7, 8, 9.

For high-skilled white-collar workers, the distribution is dominated by terms related to software applications, network design, analytical thinking, digital data handling, communication, planning, management, and willingness to learn. Character and social skills also appear frequently. The prevalence of bigrams suggests greater complexity in required skill sets. For low-skilled white-collar workers, key terms include Microsoft Office, spreadsheets, analytical thinking, data management, planning, communication, a range social and character skills.

High-skilled blue-collar roles emphasize skills related to Microsoft Office, software tools, analytical thinking, communication, monitoring, machine operation, equipment repair, and information management–skills largely tied to production processes and complemented by character traits such as independence and willingness to learn. For low-skilled blue-collar workers, the distribution centers on unigrams related to team management, product handling, communication, system operation, technical drawing, documentation, and basic software tools. Traits like motivation and compliance with legal and quality standards complement–but do not dominate–the skill profile.

Although word clouds offer a visual summary of frequent terms, they reveal little about the latent structure of skill demand. Many skill groups remain obscured due to restrictions on the number of unigrams and bigrams displayed for readability. To address this limitation, I apply unsupervised topic modeling to reduce the dimensionality of the skill data and uncover underlying patterns (Arora et al. 2012). Specifically, I use BERTopic, a method that combines transformer-based embeddings with class-based TF-IDF to extract coherent topics from text corpora (Grootendorst 2022; Sammut and Webb 2011). In labor economics, BERTopic has proven effective in applications such as job matching, vacancy classification, and skill–wage estimation (Boukari and Faiz 2024; Mankolli 2022; Ao et al. 2023).

In this setting, each occupational group is treated as a document composed of non-conceptualized extracted skills. BERTopic generates 20 latent topics per group,

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[8] This difference likely reflects occupational scope: STEM vacancies typically have more skill-intensive demand. See Table 2 for comparisons across STEM and non-STEM skill demands.

[9] I experimented with trigrams and four-grams, but their low relative term frequency contributed only minimal additional information to each word cloud distribution.

each comprising a representative set of skills. I select 10 representative terms from each topic and use the ChatGPT-4o model to assign concise, human-readable labels to them. The resulting skill categories–visualized in Figs. 10, 11, 12, 13, and 14–are markedly more informative than word clouds. Subsequently, I embed these topics using UMAP, which reduces high-dimensional graphs to two dimensions (McInnes et al. 2018). I then cluster them via HDBSCAN by McInnes et al. (2017) to identify semantically dense regions, with each cluster color-coded accordingly.

For high-skilled white-collar workers, skill topics reflect advanced competencies: proficiency in multiple foreign and programming languages, database and network administration, financial oversight and transaction execution, and AI-related skills such as cloud computing. These are complemented by social and character traits, including effective communication, behavioral flexibility, critical thinking, and analytical reasoning. Among low-skilled white-collar workers, topics emphasize fluency in English, creative writing, Microsoft Office proficiency, data analysis, digital collaboration tools, event planning, legal compliance, driving, and record-keeping–alongside interpersonal skills such as customer service, attention to detail, forward-thinking, and willingness to learn.

High-skilled blue-collar workers show demand for foreign language skills in customer contexts, digital productivity tools, technical writing and documentation, and a wide range of production-related competencies: equipment maintenance (electrical, heating, medical), IT troubleshooting, and financial transaction handling. These are paired with interpersonal attributes such as stress tolerance, teamwork, adaptability, and task planning. For low-skilled blue-collar workers, topics center on operational and logistical tasks: record-keeping, goods handling, installation monitoring, driving, cleaning, mechanical precision, and data integration using SAP and spreadsheets. Soft skills such as behavioral flexibility, stress management, and analytical thinking also appear across topics.

Overall, skill topics across occupational groups show internal coherence with modest variation across clusters. White-collar roles–especially among managers, professionals, and technicians–are characterized by cognitive and interpersonal skills, which have become increasingly salient with digitalization. As noted by Autor et al. (2003), these non-routine analytical tasks typically require domain-specific expertise, distinguishing white-collar from blue-collar work. In contrast, blue-collar occupations, historically grounded in physical and operational skills, now increasingly demand greater technical fluency. Empirical studies by Cappelli (2015); Hershbein and Kahn (2018); Handel (2016) document rising demand for programming, digital troubleshooting, and interaction with automated systems, reflecting the technological transformation of manual labor in advanced manufacturing and logistics.

While this exercise offers a descriptive overview of skill demand across occupational groups, the resulting skill topics–derived from non-conceptualized text–lack semantic consistency, complicating interpretation and cross-group comparisons. This limitation arises from the absence of a standardized mapping to conceptual skill categories. As a result, the outputs are sensitive to n-gram selection and to the number of extracted topics. Among the contributions of this paper is the effort to address these challenges by implementing the classification algorithm introduced in Sect. 2.2, which systematically maps unstructured vacancy content into coherent, interpretable skill categories.

Table 4 presents summary statistics for the main outcome variables and vacancy-level features, including advertised wages, exposure to automation technologies (AI, machine learning, software, and robotics), and counts of skills classified into conceptual categories based on the taxonomy proposed by Bennett et al. (2022). The exposure scores are standardized before merging with the job vacancy data to ensure objective interpretation. As a result, they do not have a zero mean and a standard deviation of one. Notably, mean exposure is highest for software, AI, and machine learning technologies. This contrasts with the lowest exposure for robotics, attributed to the predominant presence of white-collar occupations in online job vacancies. As I documented previously, my sample systematically underrepresents blue-collar occupations, as shown in Fig. 6. This sampling bias likely contributes to the observed distribution of skill demand, particularly the lower intensity and prevalence of physical and general computer skills.

The average skill demand per vacancy reveals that cognitive skills constitute nearly one-third of total skill demand,[10] with a mean of 1.83 per vacancy. This suggests that, on average, job vacancies require high levels of cognitive skills, such as problem-solving and analytical thinking.[11] This pattern is expected given that most sought-after occupations are professional roles, as shown in Fig. 6. The second most demanded categories constitute another one-third of total skill demand and include social skills, people management, and hand–foot–eye coordination, with means of 0.65, 0.55, and 0.54, respectively. These results imply that interpersonal and physical coordination skills are highly valued in the online labor market. Conversely, language, writing, and machine learning and AI skills have the lowest means, around 0.05

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[10] Relative skill demand is defined as the sum of skill category$_k$ across all vacancies over the sum of all skill categories$_K$.

[11] Textual descriptions of each skill category are in Table 3.

per vacancy. For example, machine learning and AI skills constitute 0.076 of overall skill demand, closely matching Alekseeva et al. (2021)'s estimate of 0.07 for the U.S. in 2019.

The left-skewed distribution of skill demand suggests that most vacancies require low levels of many skills, while only a minority demand them at high levels. This pattern likely reflects the fact that only a few skill categories–such as social, cognitive, character, and hand-foot–eye coordination skills–are considered essential across a broad range of job postings. In contrast, more specialized skills, including software-specific, customer service, financial, and machine learning/AI skills, are in high demand only within particular roles. Meanwhile, physical and general computer skills tend to show both low overall demand and intensity.

To explore variations in skill demand across occupational groups, Figs. 15, 16, 17 present the hierarchical share of skill demand per group. Each skill category is represented by a proportional rectangle. The results indicate that cognitive skills dominate both high- and low-skilled roles across all occupational groups. Among white-collar high-skilled jobs, social, software-specific, and management skills are also prominent, along with character, customer service, financial, and machine learning and AI skills. In contrast, physical, writing, and language skills appear less frequently. Notably, demand for machine learning and AI skills is minimal among service and sales workers and plant and machine operators, suggesting a negative correlation with educational attainment, as these roles typically require lower levels of formal education. This is noteworthy since these groups could benefit significantly from AI adoption in the future, as suggested by Acemoglu (2024).

For low-skilled white-collar workers, character, software-specific, people management, and physical coordination skills are prominent. High-skilled blue-collar jobs emphasize cognitive, social, and physical coordination skills, as well as software-specific and management skills. In contrast, low-skilled blue-collar roles show relatively high demand for management skills among plant operators, but lower levels in elementary occupations. Character skills and finger dexterity are also sought after, reflecting patterns also observed in professional roles.

3.2 Skill premium and penalties in the online labor demand

One goal of this paper is to understand whether differences in offered pay across firms can be attributed to variation in skill demands. In line with the theoretical framework of Acemoglu and Autor (2011), the relationship between skill demand and the price of each skill can be described as follows: if the relative market price of tasks (skills) in which a particular group of workers holds a comparative advantage declines, the relative wages of that skill group are expected to fall. This prediction holds even when workers reallocate their labor to different tasks in response to changing comparative advantage, as the underlying productivity effect still applies. In this context, an increase (decrease) in skill demand leads to a corresponding rise (fall) in the relative market price.

To test these predictions in a cross-sectional setting, I examine variation in wages across job postings by firms with different skill requirements. If skill demand is a key driver of wage differentials, we should observe a systematic relationship between the types of skills required in job vacancies and the wages offered. Specifically, firms demanding skills that complement automation and technological change–such as abstract cognitive and socio-emotional skills–should offer higher wages, while firms requiring routine-intensive skills should offer lower or unchanged average wages. By analyzing how wage premia or penalties vary across different skill groups in a cross-section of job postings, I also aim to infer indirectly how past technological shifts and firms' skill needs have shaped equilibrium wage structures.

Using the previously identified in-demand skills, I explore which skill groups–cognitive, socioemotional, or manual–are associated with wage premia or penalties in online job vacancies. I estimate the wage regression outlined in Eq. (3) to identify skills with significant wage premia (positive $\hat{\beta}_k$ estimates) and those associated with wage penalties (negative $\hat{\beta}_k$ estimates). Table 6 provides initial insights into this relationship. All models are estimated using either unweighted observations (odd columns) or weighted observations (even columns), where the weights reflect the relative employment shares of occupations in the labor force.

Columns (1) and (2) include only the counts of in-demand skills in job vacancies without additional controls. These estimates reveal that social, cognitive (narrow sense), and character skills are positively and significantly associated with offered wages. For instance, a unit increase in the count of social skills is associated with an increase in wages by a factor of $exp(0.03) \approx 1.03$, or approximately 3%, significant at the 1% level. A similar pattern holds for cognitive skills. Software-specific and technical support, people management skills, financial skills, and machine learning and AI skills are associated with wage premia roughly twice this magnitude: a unit increase in demand for these skills is associated with an increase in wages of approximately 6%. In contrast, the coefficients for general computer skills are negative across all columns, suggesting a wage penalty. Skills such as hand–eye coordination, customer service, and physical abilities do not exhibit significant relationships with wages. Skill conceptual categories alone explain about 25% of the variation in wages, underscoring the central importance of skills in the literature examining wage determinants and the impacts of technological change or trade on workers.

Columns (3) and (4) incorporate controls for broad occupational groups and industries. These controls account for systematic differences in wage levels related to job type and sector. After their inclusion, the coefficients on most skill groups decline in magnitude but remain statistically significant. The explained variation in wages increases by roughly 20 percentage points, indicating that occupation- and industry-level heterogeneity accounts for a substantial share of wage differences.

Columns (5) and (6) further include observable job characteristics, such as the region of work, workplace type, involvement of temporary work agencies, contract type, and minimum education requirements. These controls help isolate the effect of skill demands by accounting for job-level attributes that may influence wages. The inclusion of these variables increases the explained variation in wages by nearly 20 percentage points. This result is broadly consistent with Deming and Kahn (2018), who find greater explanatory power when controlling for experience and education in the U.S. context. Alekseeva et al. (2021) report comparable levels of explained variation, though their specification and research design differ slightly and are not directly comparable.

Columns (7) and (8) add monthly fixed effects to control for intertemporal variation, such as seasonal trends. In the fully specified model, the coefficients on most skill groups decline further but remain strongly significant. Software-specific skills are the only category that experiences a notable decline in both magnitude and significance after the inclusion of the full set of controls. Even with these additions, skill demands continue to play an important role in explaining wage differences. Social skills, narrow-sense cognitive skills, character skills, software-specific and technical support skills, people-management skills, financial skills, machine learning and AI skills, and project-management skills maintain positive and statistically significant associations with wages. The largest skill premium is observed for machine learning and AI skills, followed by financial and people-management skills. For occupations within the same occupational group and industry (or those with the same controls as in Columns (3) and (4)), a unit increase in demand for machine learning and AI skills is associated with an increase in wages by a factor of by a factor of $exp(0.04) \approx 1.04$, or approximately 4%, significant at the 1% level. Although this is roughly half the effect estimated in Columns (1) and (2), it remains economically meaningful and aligns with the 5% AI-skill wage premium reported by Alekseeva et al. (2021) for the U.S. online labor market. Conversely, general computer skills continue to carry a wage penalty. Hand–eye coordination, writing, customer service, and physical skills remain insignificantly associated with wages. These results are robust across weighted and unweighted specifications.

The final step of this analysis is to examine whether the estimates of Eq. 3 hold across sectors. This analysis is conducted across four consolidated sectors: primary, secondary, private services, and public and social services. Table 7 presents the results of this exercise. In the odd-numbered columns, I control for broad occupational groups and industry fixed effects, while in the even-numbered columns, I include additional relevant controls along with monthly fixed effects.

Results for the primary sector show a limited number of significant coefficients. The only significant skill premia is observed for cognitive skills (narrow sense), while hand-foot-eye coordination and finger dexterity skills, despite being either non-significant or positively associated with wages across all sectors, are associated with a skill penalty in this sector.

I therefore focus on the remaining three sectors, treating the primary sector as an exception due to its small sample size. Most of the skill premia and penalties observed earlier are preserved in sector-specific estimates, but the sectoral breakdown allows us to identify which sector is driving each effect. Social and people-management skills are associated with wage premia of approximately $1-3\%$ across sectors, similar to the pooled results. Other patterns are more sector-specific. Software-specific skills are associated with a wage premium in private services, while general computer skills exhibit a weak wage penalty only in this sector. Writing and language skills are associated with wage premia of 4% and 14%, respectively, in the secondary sector, but remain insignificant in the services sectors, where they are likely implicit requirements that are universally held. The significance of language skills disappears in the fully saturated model, so this result should be interpreted with caution. This pattern likely reflects differences in the scarcity and necessity of these skills across sectors. Financial skills are valued similarly at around 4%, but only in the secondary sector and private services sectors. As expected, machine learning and AI skills are valued in private and public services but not in the secondary sector. The valuation of these skills in public and social services is notably higher, but they lose significance in the fully saturated specification and should therefore be interpreted with caution.

Based on the observations in this subsection, I find indirect evidence supporting the prediction of Acemoglu and Autor (2011). Specifically, routine and manual skills–such as hand-foot-eye coordination, finger dexterity, and other physical abilities–as well as routine cognitive skills, including customer service, language proficiency, and general computer skills, provide little to no wage premium or may even result in a skill penalty. In contrast, non-routine cognitive and socioemotional skills offer a skill premium. These include people and project management skills, social and character skills, machine learning and AI skills, as well as financial skills.

3.3 Skill demand conditional on firm-level adoption of automation technologies

Having established that vacancies requiring social interaction, character traits, people and project management, software-specific and technical support knowledge, financial expertise, and AI or machine learning capabilities are associated with higher wages. I now examine whether firms more exposed to automation technologies–proxied by the occupational structure of their labor demand–exhibit lower conditional demand for skills. This analysis builds on the framework of Acemoglu et al. (2022), who infer automation adoption from firms' hiring patterns, specifically their tendency to recruit into occupations exposed to automation.

To test this hypothesis in a cross-sectional setting, I stratify firms by their degree of automation adoption–measured through the average automation susceptibility of the occupations they seek to fill–and estimate Eq. (4). This specification evaluates whether firms at higher levels of inferred automation adoption exhibit systematically lower skill demand.

Table 8 summarizes the contrasts in conditional skill demand between firms above the 70th percentile of exposure to a given automation technology and their less-exposed counterparts. The estimates imply that, holding constant broader occupation, industry, and vacancy-level covariates, firms demanding AI- and machine learning-exposed occupations require, on average, roughly 0.17 additional cognitive skills. Firms oriented toward software-exposed occupations demand approximately 0.29 more cognitive skills, whereas those tilted toward robotics-exposed occupations require about 0.14 fewer cognitive skills.

Across nearly all specifications, firms tilted toward AI, machine learning, and software technologies exhibit systematically higher conditional skill demand across most conceptual skill categories. By contrast, firms oriented toward robotics-exposed occupations display lower conditional demand for the majority of skill groups.

There is a possibility that the observed relationship between automation and skill demand is nonlinear, and that the baseline specification primarily captures variation across technologies rather than across adoption intensities. To investigate this further, I re-estimate the model using alternative thresholds that approximate different stages of adoption–specifically, the 50th and 90th percentiles of the firms' labor demand exposure distribution. The results, reported in Table 9, reveal a hump-shaped pattern in conditional skill demand. Panel A shows that firms with moderate adoption–those above the median–exhibit higher skill requirements across most categories and all technologies, suggesting that the early and intermediate phases of automation adoption are associated with skill complementarity. However, Panel B reveals a reversal at the highest margins (extensive) of unobserved automation-technology adoption: firms in the top decile show significantly lower conditional skill demand. These findings are in line with Acemoglu et al. (2022), who suggest that firms adopting automation technologies reduce the breadth and depth of skill requirements in job postings, consistent with substitution effects. The analysis contributes to the existing literature by extending this finding to two additional technologies–software and robotics–in addition to AI.

To visualize this nonlinearity, Figs. 18, 19, 20 plot unconditional mean skill demand across percentiles of firm-level automation adoption. Demand peaks between the 60th and 80th percentiles before falling sharply at the upper tail. This pattern reinforces the interpretation that the relationship between adoption and skill demand is non-monotonic. While estimates at the lower end may reflect corner effects, the decline in skill demand among firms with extensive adoption at the upper end remains both statistically significant and substantively robust.[12]

Taken together, these results indicate that the intensity of automation adoption does not generate uniformly increasing skill demand. Instead, the relationship appears to follow a nonlinear trajectory, with skill demand rising during moderate stages of adoption but falling once adoption passes a critical threshold.[13] Accordingly, it is essential to account for adoption thresholds–beyond which firms' skill requirements appear to shift qualitatively–an issue I address more closely in the subsequent analysis.

3.4 Automation exposure conditional on composition of in-demand skills

I have shown that while firms adopting AI, machine learning, and software technologies tend to exhibit higher conditional demand for skills–consistent with skill complementarity at early and intermediate stages of

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[12] Confidence intervals (not shown) suggest greater uncertainty at the lower tail due to sparser support, while estimates at the top of the distribution are more stable. See Table 9.

[13] This analysis is based on job vacancy data, which reflect stated demand for skills in posted ads but not necessarily internal worker redeployment or informal hiring. Firms with extensive adoption and lower observable skill demand may still depend on those capabilities through internal reallocation, offline channels, or interfirm outsourcing of skill-intensive tasks, as documented by Goldschmidt and Schmieder (2017). Such mechanisms are not visible in vacancy-level data but may shape the realized distribution of skill inputs.

adoption–this relationship reverses at the highest margins of extensive automation-technology adoption. The resulting hump-shaped pattern suggests that beyond a certain threshold, automation reduces skill intensity of job postings, particularly in robotics-intensive firms. I now turn to the relationship between the composition of in-demand skills and exposure to distinct automation technologies.

More concretely, I estimate whether the presence of specific skill groups in job postings is systematically associated with lower levels of automation exposure. This analysis aims to identify which skills may serve as a shield against automation by being associated with lower occupational susceptibility to technological substitution.

The relationship between skills and exposure to automation technologies is inherently complex. Skills may interact with automation through either substitution or complementarity. Complementary skills are typically in higher demand within occupations more exposed to automation, as they are essential for the implementation, operation, and maintenance of these technologies. In contrast, substitute skills tend to be more prevalent in occupations less exposed to automation, as they underpin tasks that remain difficult to automate. Moreover, skill requirements evolve with technological change. As shown by Bessen (2015), automation often leads to task reallocation within jobs rather than pure substitution, complicating the interpretation of observed patterns in skill demand and exposure. As discussed earlier, firms at the frontier of automation technology adoption exhibit lower conditional demand for skills, a pattern also documented by Acemoglu et al. (2022). This finding aligns with the broader argument in Acemoglu and Autor (2011) that the demand for routine tasks has declined substantially over the past three decades due to competition from information technologies, while demand has risen for abstract and non-routine manual tasks that complement routine work that is increasingly executed by capital.

To examine how skills interact with exposure to automation technologies, I follow a three-step approach. First, I estimate regressions of occupational exposure to automation on counts of in-demand skills. Second, I extend the model by including interaction terms between specific skills and social skills–which are assumed to be difficult to automate–in order to assess how skill combinations relate to exposure. Third, I estimate the average treatment effects (ATEs) of in-demand skills on automation exposure, accounting for potential selection into skill demand based on observed vacancy characteristics and a proxy for firm-level adoption of automation technologies, inferred from the occupational composition of firms' hiring patterns.

Table 10 reports results for exposure to AI and machine learning. Controlling for broad occupational group, industry, and the full set of covariates, I find that a one-unit increase in demand for hand–foot–eye coordination skills is correlationally associated with a 0.01 standard deviation reduction in exposure to this technology. The same model predicts a negative association for machine learning and AI skills, but with a magnitude approximately four times larger (around 0.04 standard deviations). This skill group is not only linked to lower exposure to AI and machine learning but is also associated with reduced exposure to software and robotics technologies (see Tables 11 and 12). The observed wage premia for machine learning and AI skills point to both their scarcity in the labor market and their potential to shield occupations against automation.

Results for software-related exposure, presented in Table 11, broadly mirror those for AI and machine learning, though some notable differences emerge. Social skills are correlationally associated with higher software exposure in the baseline models, but this relationship becomes statistically insignificant once additional controls are introduced. Customer service skills are positively correlated with exposure–likely reflecting either the increasing automation of tasks in sales, marketing, and call center environments, or their complementarity to these technologies. This skill group lacks associated wage premia, suggesting a relatively high supply of such capabilities in the labor market.

Table 12 presents estimates for robotics-related exposure. The patterns remain consistent: previously discussed skill groups–namely hand–foot–eye coordination and machine learning and AI skills–are negatively associated with exposure to this technology. Additionally, software-specific skills now show a strong and statistically significant negative association, potentially shielding occupations from mechanization-type automation technologies.

Language skills are consistently associated with higher exposure across all automation technologies. One explanation is technological: many-to-many tasks–such as machine translation, sales communication, marketing outreach, and call center interactions–are particularly well-suited to automation via machine learning and software, and are thus more widely automated. This contrasts with the negative association observed for skills like hand–foot–eye coordination, which are inherently more difficult to automate due to their reliance on physical dexterity in unstructured environments.

An alternative and more plausible interpretation is institutional. Mentions of language skills in job postings may indicate roles intended for foreign or migrant workers.[14] In such a case, the positive association between language skills and automation exposure may reflect labor market segmentation, whereby migrant workers are disproportionately hired into occupations more susceptible to automation. This interpretation aligns with the findings of Mann and Pozzoli (2024), who show that firms often allocate migrant labor to tasks that are both routine and automatable, and may be more readily substituted as automation technologies diffuse. This pattern suggests that language skills may partly proxy for migrant-targeted roles concentrated in automatable tasks, making this an important direction for future research.

To examine sectoral heterogeneity, Table 13 reports regressions of occupational exposure to automation on counts of in-demand skills, estimated separately for each sector. The models follow the specification in Eq. (5), including fixed effects for occupation, industry, and month, as well as detailed vacancy-level controls. Results are disaggregated across three broad sectors: (i) primary and secondary (agriculture, manufacturing, construction), (ii) private services (IT, retail, finance), and (iii) public and social services (education, healthcare, administration), as defined in Table 5.

The estimates reveal substantial sectoral heterogeneity in the correlational relationship between skill demand composition and automation exposure. In private services, for instance, hand–foot–eye coordination and finger dexterity skills are negatively associated with exposure, while language and customer service skills are positively associated with exposure to software technologies. In public services, physical and coordination skills also exhibit strong negative relationship with exposure, and both software-specific and project management skills are similarly linked to lower exposure levels. Additionally, in private services, demand for software-specific skills is negatively associated with exposure to robotics, reinforcing the interpretation that software-intensive roles involve cognitive and interpersonal tasks that are less susceptible to physical automation.

Nonetheless, these patterns should be interpreted cautiously. Some negative associations may reflect sectors where automation is less prevalent, hence the causality may run in the opposite direction. Furthermore, variation in the substitutability or complementarity between skill-machine capabilities–unobserved in this analysis–could partly explain the estimated relationships. I partly address these concerns in the following discussion.

Building on the framework of Autor et al. (2003); Deming (2017), which highlights that computers (machines) excel at routine, codifiable tasks but struggle with interpersonal ones, I examine whether automation exposure depends on the interplay between in-demand skills and social skills. Specifically, I introduce interaction terms between each in-demand skill group and social skills, widely considered difficult to automate. This extension improves the measurement strategy by clarifying whether observed patterns reflect skill–machine substitutability or complementarity. As Acemoglu and Autor (2011) argue, neglecting such interactions may obscure underlying mechanisms, especially when opposing effects offset one another.

Table 14 presents main and interaction effects estimated from Eq. (6). All regressions include occupation, industry, and time fixed effects, along with detailed vacancy-level controls.

Several main effects reinforce the earlier results. The effect sizes remain modest, yet they are systematically larger than previous estimates in Tables 10, 11, 12, suggesting that the earlier coefficients were biased downward–some even offsetting each other. The strongest shielding effects arise from machine learning and AI skills, as well as from financial skills, with magnitudes implying a 0.04–0.11 reduction in exposure across all automation technologies. Demand for hand–foot–eye coordination skills is negatively correlated with exposure to software and robotics, consistent with their limited substitutability by existing technologies. Likewise, software-specific skills are negatively associated with robotics exposure, indicating a shielding effect insofar as these skills tend to be concentrated in occupations that are less exposed to robotics.

Interaction effects provide further nuance. They generally amount to $20-50\%$ of the size of the main effects, indicating that complementarities with social skills attenuate–but do not overturn–the shielding properties of the previously identified skill groups. Positive and statistically significant coefficients on the interactions between physical and social skills–particularly for AI, machine learning, and software–suggest that manual tasks combined with interpersonal requirements are more likely to complement automation technologies, as these bundles tend to characterize occupations with higher exposure. A similar pattern holds for financial and social skills, consistent with task reallocation in which automation substitutes for routine components while human labor increasingly concentrates on interpersonal functions (Bessen 2015). Likewise, the interaction between machine learning and social skills predicts higher robotics exposure, pointing to complementarities in roles that bundle advanced technical and relational capabilities. By contrast, some skills–such as writing skills–exhibit negative interaction terms,

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[14] For example, consider a vacancy that states: 'This position is available for German, French, Ukrainian, or Hungarian applicants.' The skill extraction process and its mapping to the conceptual skill taxonomy, as described in Sect. 2.2, classify such phrases as language skills due to their semantic proximity to this category, even though they may reflect the targeting of foreign workers rather than genuine language proficiency requirements.

suggesting that workers possessing these skills are less likely to be subsequently employed in occupations highly exposed to robotics technologies.

Sector-specific results in Table 15 extend this analysis. In primary and secondary sectors, people management and character skills are positively associated with exposure, implying complementarity in supervisory and technical roles. In contrast, physical and hand–foot–eye coordination skills remain negatively associated with exposure, reinforcing their shielding role. In public and social services, results are generally weaker, though financial skills continue to exhibit negative associations. The interaction term between machine learning and social skills are positively associated with exposure across all technologies, particularly in administrative and healthcare settings. Meanwhile, customer service and social skills show negative interaction effects, possibly reflecting strong resistance to automation in human-centric roles.

Table 1 Average Treatment Effects of Skill Presence on Automation Exposure to Technology τ

	ATE$^{\text{AI and ML}}$	ATE$^{\text{Software}}$	ATE$^{\text{Robotics}}$
Social skills	0.018** (0.002)	0.030** (0.003)	0.011** (0.003)
Cognitive skills (narrow sense)	0.000 (0.003)	0.008* (0.003)	−0.021** (0.004)
Character skills	0.008** (0.003)	0.022** (0.003)	0.017** (0.003)
Hand-foot-eye coordination skills	−0.023** (0.002)	−0.025** (0.002)	−0.021** (0.003)
Finger dexterity skills	0.005+ (0.003)	0.010** (0.003)	0.011** (0.003)
Software-specific skills	−0.046** (0.006)	−0.030** (0.006)	−0.070** (0.007)
People management skills	−0.018** (0.003)	0.001 (0.003)	−0.029** (0.004)
Writing skills	−0.029* (0.014)	0.008 (0.015)	−0.003 (0.016)
Customer service skills	0.030** (0.004)	0.049** (0.004)	0.040** (0.005)
Physical skills	−0.029+ (0.015)	−0.023 (0.017)	−0.025 (0.020)
Financial skills	−0.054** (0.009)	−0.040** (0.009)	−0.068** (0.010)
Machine Learning and AI skills	−0.052 (0.033)	−0.030 (0.031)	−0.042 (0.041)
Project management skills	−0.023* (0.009)	0.000 (0.010)	−0.004 (0.010)
Language skills	−0.029 (0.019)	−0.024 (0.022)	−0.052* (0.022)
Computer general skills	−0.003 (0.019)	0.029 (0.020)	0.013 (0.019)
N	324,377	316,508	316,508

Firm's labor demand exposure to automation technologies τ' and τ'' decile, broad occupational group (ISCO-1d), industry (NACE-1d), region, and minimal education level included as controls. Robust standard errors are in the parentheses. $^{**}\,\mathrm{p} < 0.01, ^{*}\,\mathrm{p} < 0.05, +\,\mathrm{p} < 0.1$

Taken together, the results suggest that while some skills consistently shield against automation, complementarities emerge in tasks that bundle both technical and social competencies–especially in service-oriented sectors. Still, negative associations may partly reflect lower overall skill requirements in less-automated firms or sectors, a possibility that I examine in the final part of the analysis.

To identify the relationship between in-demand skills and automation exposure in the context of the preceding findings, I apply an inverse probability weighting estimator, as described in Sect. 2.4. This method reweights observations based on the estimated probability of treatment—that is, the presence of a given skill in a vacancy conditional on observed vacancy characteristics. Treatment probabilities are estimated based on occupation, industry, education, region, and adoption of automation technologies-proxied by the decile of firm-level labor demand exposure to the *other* two technologies, $\tau \neq \tau' \neq \tau''$.

Table 1 reports the resulting average treatment effects (ATEs) separately for exposure to AI and machine learning, software, and robotics. The estimates exhibit both positive and negative signs, consistent with the theoretical framework of Acemoglu and Autor (2011). Negative ATEs indicate that vacancies requiring a given skill are causally associated with lower occupational exposure to automation–measured in standard deviation units–suggesting these skills act as a shield against automation, under the assumption of conditional unconfoundedness.[15] Positive ATEs, by contrast, suggest that these skills are disproportionately present in occupations more exposed to automation, potentially reflecting a complementary relationship–where the skill is necessary to implement, supervise, or collaborate with a given technology.

To illustrate, an ATE of 0.018 for social skills under AI and machine learning exposure implies that vacancies requiring social skills exhibit, on average, 0.018 standard deviations higher exposure to this technology than similar vacancies in other observables not requiring those skills. Conversely, an ATE of -0.046 for software-specific skills indicates that these vacancies are associated with 0.046 standard deviations lower AI exposure, conditional on observed characteristics.

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[15] As discussed earlier, several potential confounding factors may bias the estimated relationship between skills and automation exposure, such as intrafirm insourcing or interfirm outsourcing of skill-intensive tasks, which are often correlated with technology adoption. I do not observe sufficient firm-level variables to directly control for these channels. Additional vacancy-level controls not included in the main specification appear to have only marginal explanatory power. Including all available covariates as matching variables leads to sample fragmentation and unstable estimates due to limited support across covariate combinations.

The resulting ATEs reveal a clear divide. Manual and non-routine abstract skills–such as physical skills, hand–foot–eye coordination, software-specific skills, people- and project-management skills, and financial skills–are negatively associated with exposure to at least one of the respective technologies. This suggests that these skills act as a shield against current automation technologies, in line with the framework of Acemoglu and Autor (2011). Surprisingly, machine learning and AI skills, despite previously showing significant correlational associations, now lack significance–likely due to their scarcity and the left-skewed distribution of firms' technology adoption. As predicted by Acemoglu and Autor (2011), routine skills located in the middle of the skill distribution–such as customer service skills, narrow-sense cognitive skills, and finger dexterity–are positively associated with automation exposure across all technologies, suggesting that these skills are more susceptible to automation. Social and character skills are also positively associated with exposure, suggesting they play a complementary or implementation role (Bessen 2015; Deming 2017).

The negative estimates offer a clear normative interpretation, as they suggest that certain skills may serve as a shield against automation. Positive estimates require more nuance: they may reflect interpersonal capabilities difficult to automate–such as social and character skills–or routine tasks, which are more easily displaced by automation.

As a robustness check, I re-estimate ATE_k^{τ} including decile indicators for offered wages as an additional matching variable. This controls for the sorting of workers into more productive firms, as emphasized by Borovičková and Shimer (2017) and Lochner and Schulz (2024). Results, reported in Table 16, remain virtually unchanged, reinforcing the interpretation that findings are not driven by unobserved firm or worker characteristics.

Table 17 presents estimates using the augmented IPW (AIPW) estimator, which addresses potential instability of weights in standard IPW models when treatment probabilities are close to zero. These results are consistent with the original findings, confirming the robustness of the estimates.

Still, technological change is dynamic and the task space is constantly evolving, as emphasized by Bessen (2015). Skills currently associated with greater exposure–such as customer service, hand–foot–eye coordination, or cognitive skills in the narrow sense–may become obsolete as new technologies mature. Workers relying on these skills may face increasing displacement risks unless they upskill or reskill. As illustrated by the bank teller example in Bessen (2015), automation may eliminate routine tasks while reallocating work toward interpersonal roles. Thus, interpersonal skills–particularly social and character skills–may retain their comparative advantage over automation technologies for a longer period of time.

4 Conclusions

This paper examined how firms' in-demand skills relate to occupational exposure to automation technologies–AI and machine learning, software, and robotics–using a cross-sectional dataset of Slovak online job vacancies posted in 2022. Unstructured vacancy texts were algorithmically processed and mapped into fifteen conceptual skill categories nested within cognitive, socioemotional, and manual domains, enabling consistent skill comparisons across occupations.

First, I documented strong and systematic variation in skill requirements across occupational groups. White-collar roles concentrated demand on cognitive, socioemotional, and software-specific skills, while blue-collar occupations exhibited demand for procedural, physical, and technical troubleshooting skills. Wage regression estimates showed that scarce, high-value skills–particularly machine learning, AI, project and people management–were associated with wage premia, whereas routine manual and general computer skills were linked to wage penalties or insignificant returns. These findings were consistent across most sectors, though sector-specific estimates revealed that some skill–wage relationships were highly contextual.

Next, I examined whether firms closer to the frontier of automation technology adoption–proxied by the average exposure derived from the occupational structure of their labor demand–differed systematically in their overall demand for skills. For this purpose, the paper introduced a new Europe-specific measure of occupational exposure to AI, machine learning, software, and robotics. I constructed this measure by using semantic similarity between patent texts and task-level occupational descriptions. The results uncovered a hump-shaped relationship between firm-level automation exposure and conditional skill demand across most skill groups. Firms at intermediate levels of automation adoption posted the highest number of required skills, while those at the top of the exposure distribution exhibited lower demand. This non-monotonic pattern, present across all technologies, suggested that automation may first complement and later substitute for human capabilities as firms progressed along the adoption frontier.

Turning to the composition of in-demand skills, I then analyzed how specific skill groups were associated with occupational exposure to automation. Skills such as hand–foot–eye coordination, financial skills, machine learning and AI skills, and software-specific skills were consistently negatively correlated with exposure across all technologies. Conversely, language and customer service skills were positively associated with exposure. One plausible explanation is institutional: these skills may have served as a proxy for migrant-targeted vacancies in routine, automatable roles, reflecting underlying segmentation in the labor market.

To distinguish skill–machine substitution from complementarity, I introduced interaction terms between in-demand skills and social skills–assumed to be inherently difficult to automate. The results showed that technical and financial skill bundles that, when combined with social abilities, were positively associated with exposure, suggesting that they complemented automation rather than shielding against it. Yet across most domains, the magnitude of the main effects exceeded that of the interaction terms, indicating that many skills retained their shielding properties when demanded independently.

Finally, to strengthen the interpretation of observed relationships, I implemented an inverse probability weighting estimator that reweighted the vacancies based on treatment probabilities, conditional on observed vacancy characteristics and firms' adoption of automation technologies–proxied by deciles of firm-level labor demand exposure. The estimated average treatment effects offered a clear divide: abstract and manual skills–including software-specific, physical, people-management, and financial abilities–were consistently negatively associated with automation exposure, consistent with a shielding interpretation. Routine cognitive and customer service skills were positively associated with exposure, while social and character skills–despite being difficult to automate–were also concentrated in more exposed occupations, likely reflecting complementarity in supervisory or interpersonal tasks.

In the end, even as technological change reshapes the demand for specific skills–rendering some increasingly automatable and others more resilient–human adaptability remains essential. Workers are not passive recipients of these shifts: by cultivating interpersonal capabilities that complement machine intelligence and reskilling in response to the evolving task space, they can preserve their comparative advantage and actively reshape their roles in ways that harness, rather than resist, the forces of automation–even in ways that remain difficult to anticipate.

The data, sequences, and methods developed in this paper offer a foundation for future research on how automation technologies shape labor markets in the European context. Follow-up studies could extend beyond online vacancy data to examine how automation exposure influences wages, employment, and reallocation across industry–occupation cells using representative datasets. The estimated exposure scores could inform future researchers about whether emerging AI technologies compress or polarize the wage distribution, especially regarding the college wage premium (Autor et al. 2024; Bloom et al. 2025; Gonzalez Ehlinger and Stephany 2023; Acemoglu 2024).

Future research could also refine the design of occupational exposure measures beyond dictionary-based classification of patent texts by focusing on functions where AI and machine learning or robotics have recently advanced, such as service robotics, computer vision, or creative content generation. Researchers armed with longitudinal, multi-country online vacancy panels could construct proxies for establishment-level technology adoption–e.g., the share of AI- or robotics-related skills in posted vacancies–and estimate its effects on wages, skill premia, or productivity, following the approaches of Acemoglu et al. (2022); Alekseeva et al. (2021); Gonschor et al. (2025).

In light of this paper's finding that language skills are consistently associated with higher automation exposure, future work should also explore the institutional dimension of labor market segmentation. I hypothesize that demand for language skills may partly reflect firms' targeting of migrant workers, who were disproportionately hired into routine and automatable roles. Investigating the intersection of migration and technological change–particularly whether automation technologies substitute for or complement migrant labor–would be a valuable direction for future studies, following the example of Mann and Pozzoli (2024).

While this paper focused on labor demand, future work could examine the supply side. Researchers with access to application or resume data could test whether posted skill requirements influence applicant quality or match outcomes, following the design in Balgova et al. (2023). Additionally, future studies could investigate whether the diffusion of generative AI alters or uniformly shift the composition of skill demand and skill premia within conceptual categories across firms.

Although limited to a single country and time period, the empirical patterns uncovered in this paper–on skill premia, automation exposure, and firm-level adjustment–are consistent with findings from other high-income industrialized economies.

Appendix

See Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 20 and Tables 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and 17.

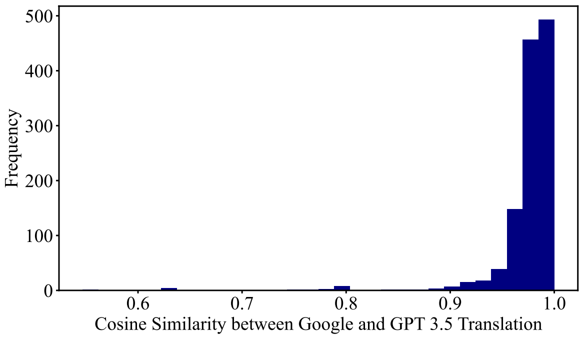


Fig. 4 Histogram of pairwise cosine similarity between Google Translate and GPT 3.5 Turbo translation obtained by embeddings from JoBERT model

Table 2 An illustrative example of the skills extraction depicted in Fig. 1

Online job vacancy ID: 5368355	
In what area will you work? The projects are focused on the issue of heart rhythm disorders and the prevention of heart failure, developed by the leading scientific and technological company CertiCon. We apply the knowledge of experts and develop solutions that improve and simplify the lives of millions of people around the world. The unique added value is our own applied research and cooperation with international institutions. We are currently working on building infrastructure in Azure DevOps and AWS Amazon Web Services cloud services We are looking for a new colleague to our team for the position of DevOps Engineer who will help us with the process of migrating our development and production environments to cloud services What exactly are you going to do? Implementation, deployment and support of Azure DevOps and AWS environments Collaborate with developers to integrate new system components Infrastructure monitoring, analysis of problems and performance characteristics Creating and testing CI CD scripts What development environment do we use? Azure DevOps AWS Docker Kubernetes Kafka HBase What technologies we use Azure DevOps AWS Docker Kubernetes Kafka Hbase Requirements for a new team member MUST HAVE JSON YAML GIT Docker Swarm Kubernetes Knowledge of CI CD automation tools, e.g. Jenkins, Azure DevOps TeamCity Knowledge of a cloud platform such as AWS Azure GCP Knowledge of a scripting language, e.g. SH Bash PowerShell Batch Basics of network connection reverse proxy server client server certificates X 509 standard Also at least at level B with a focus on technical English communication with customers and teams abroad NICE TO HAVE Knowledge of Linux or Windows operating system Knowledge of SQL language Knowledge of relational databases, eg MS SQL Postgre SQL MySQL Knowledge of virtualization platforms such as VMware OAuth2 OpenID Connect or SAML 2 0 authorization authentication protocols	
Extracted ESCO skills	Mapped conceptual category skills

Table 2 (continued)

Online job vacancy ID: 5368355	
● Jenkins CI ● SQL ● installing structural masonry materials ● DevOps ● dock operations ● postgres ● SQL ● developing solutions ● migration ● DevOps ● cloud technologies ● technical or academic writing ● using digital tools for collaboration and productivity ● monitoring ● internal migration ● cloud technologies ● operate relational database management system ● allocating and controlling physical resources ● performance analysis techniques ● technical language ● software and applications development and analysis ● cloud computing ● software and applications development and analysis	● Cognitive skills (narrow sense) ● Software (specific) skills and technical support ● Finger dexterity skills ● Cognitive skills (narrow sense) ● Cognitive skills (narrow sense) ● Software (specific) skills and technical support ● Software (specific) skills and technical support ● Cognitive skills (narrow sense) ● Cognitive skills (narrow sense) ● Cognitive skills (narrow sense) ● Machine Learning and AI skills ● Writing skills ● Cognitive skills (narrow sense) ● Finger dexterity skills ● Cognitive skills (narrow sense) ● Machine Learning and AI skills ● Software (specific) skills and technical support ● Hand-foot-eye coordination skills ● Cognitive skills (narrow sense) ● Cognitive skills (narrow sense) ● Cognitive skills (narrow sense) ● Machine Learning and AI skills ● Cognitive skills (narrow sense)
Online job vacancy ID: 5367527	
You participate in the production of new vehicles in various operations You assemble individual parts into vehicles You work according to the work standard You perform maintenance level 1 minor work within your responsibility You ensure order in your workplace You participate in continuous improvement Primary or secondary education, study certificate, high school diploma, even without previous experience Experience in the production process is an advantage, technical knowledge in the field of cars is welcome Willingness and desire to work on shifts Reliability and flexibility manual dexterity Ability to respond quickly and promptly Motivation and interest in permanent employment at PSA	
Extracted ESCO skills	Mapped conceptual category skills

Table 2 (continued)

Online job vacancy ID: 5367527	
• motor vehicle • vehicle production process • continuous improvement strategies • meet commitments	• Finger dexterity skills • Hand-foot-eye coordination skills • Social skills (including agreeableness and extraversion) • Character skills (conscientiousness, emotional stability and openness to experience)

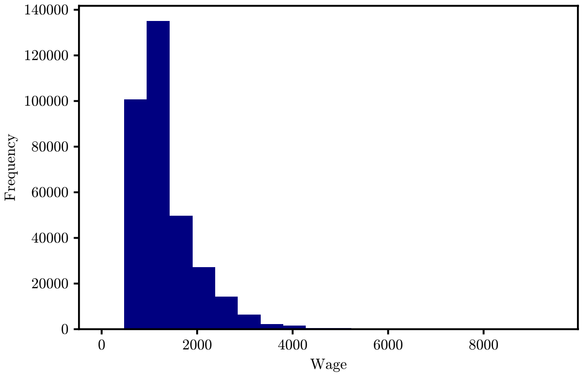


Fig. 5 Nominal wage distribution in online job vacancies, Slovakia, 2022.
Source: Profesia data

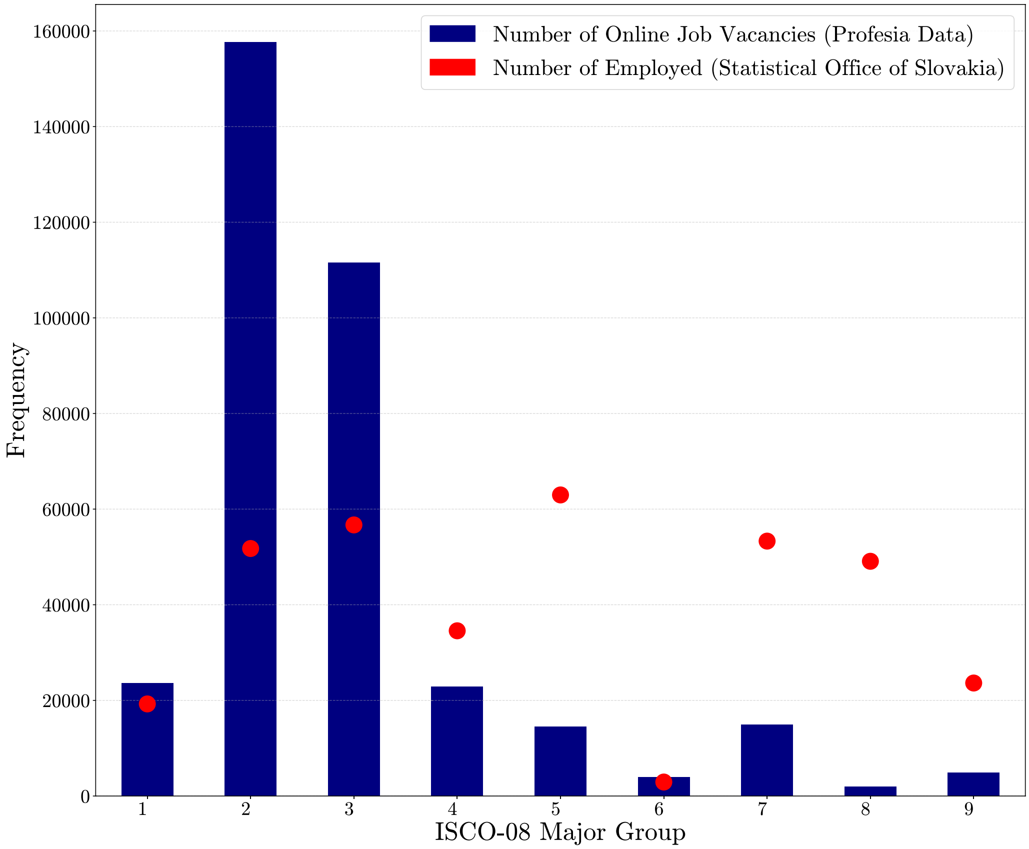


Fig. 6 Frequency of online job vacancies (blue bars) and relative frequency corresponding to representative sample of employment across ISCO-08 (red dots) major group. Source: Profesia data, Statistical Office of Slovakia. 1. Managers; 2. Professionals (Health; Teaching; Business and Administration; Information and Communications Technology; Science; Legal, Social and Cultural); 3. Technicians and Associate Professionals; 4. Clerical Support Workers; 5. Service and Sales Workers; 6. Skilled Agricultural, Forestry and Fishery Workers; 7. Craft and Related Trades Workers; 8. Plant and Machine Operators, and Assemblers; 9. Elementary Occupations

Table 3 Description of conceptual skill category created in Bennett et al. (2022)

Conceptual skill category	Description
Cognitive skills (narrow sense)	Problem solving, research, analytical, critical thinking, math, statistics
	Mathematics, adaptability, direction, control, planning
	Data analysis, data engineering, data modelling, data visualization, data mining, data science, predictive analytics, predictive models
	Analyse, design, devising rule, evaluate, interpreting rule, sketch
	Calculation
	Bookkeeping, correcting, measurement
	Information processing, decision making, generation of ideas, memory
Computer (general) skills	Computer, spreadsheets, common software, Excel, PowerPoint
	Computer literacy, Internet skills, Word, Outlook, Office, Windows
Software (specific) skills and technical support	Programming language or specialized software, Java, SQL, Python, R, Stata
	Computer installation, computer repair, computer maintenance, computer troubleshooting, web development, site design
Machine learning and AI	Artificial intelligence, machine learning, decision trees, apache hadoop, Bayesian Networks, Automation Tools, Neural Networks, Support Vector Machines (SVM), Supervised learning, TensorFlow, MapReduce, Splunk, Convolutional Neural Network (CNN), Cluster Analysis
Financial skills	Budgeting, accounting, finance, cost
Writing skills	Writing
	Editing, reports, proposals
Language skills	Albanian, Arabic, Basque, Belarusian, Bosnian, Breton, Bulgarian, Catalan, Croatian, Czech, Danish, Dutch, English, Estonian, Faroese, Finnish, French, Galician, German, Greek, Hungarian, Icelandic, Irish, Italian, Latvian, Lithuanian, Luxembourgish, Macedonian, Mandarin, Maltese, Norwegian (Bokmål and Nynorsk), Polish, Portuguese, Romanian, Russian, Serbian, Slovak, Slovenian, Spanish, Swedish, Ukrainian, Welsh + language
Project management skills	Project management
Character skills	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic
(conscientiousness, emotional stability and openness to experience)	Self-starter, initiative, self-motivated
	Competent, achieving, hardworking, reliable, punctual, resistant to stress, creative, independent
Social skills	Communication, teamwork, collaboration, negotiation, presentation
(including agreeableness and extraversion)	Team, persuasion, listening
	Flexibility, empathy, assertiveness
	Advice, entertain, lobby, teaching
	Interact with others, verbal abilities
People management skills	Supervisory, leadership, management (not project), mentoring, staff
	Staff supervision, staff development, performance management, personnel management
Customer service skills	Customer, sales, client, patient
	Persuading, selling
	Advertise, sell, buy, purchase
	Repetitive customer service
Finger dexterity skills	Picking, sorting, repetitive assembly, mixing ingredients, baking ingredients, sewing and decorative trimming, operating tabulating machines, packing agricultural produce
	Control, equip, operate
	Repetitive movements
Hand-foot-eye coordination skills	Attending cattle, attending other animals, driving to transport passengers, driving to transport charge, piloting airplanes, pruning and treating ornamental and shade trees, performing gymnastic feats, performing other sports requiring skill and balance
	Accommodate, renovate, repair, restore, serving, cleaning
	Reaction on time, fine manipulations
Physical skills	Resistance, time dedicated to walking and running, carrying heavy loads

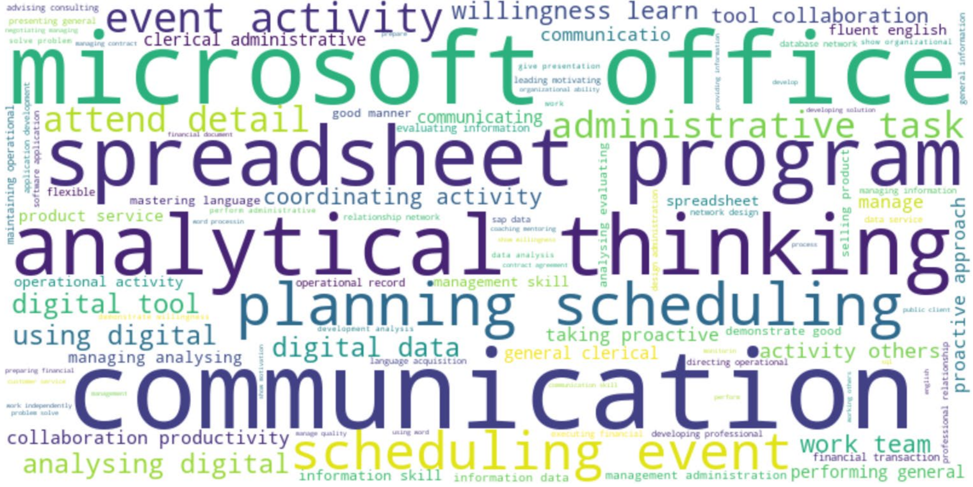

ISCO 1 - Managers

ISCO 2 - Professionals

ISCO 3 - Technicians and Associate Professionals

Fig. 7 Word clouds by ISCO Major Groups (1–3). This figure displays word clouds representing up to 100 skills within each ISCO major occupational group. The size of each skill corresponds to its relative frequency within the group. Skills are in lemmatized form, and stopwords have been removed. Source: Profesia data

ISCO 4 - Clerical Support Workers



ISCO 5 - Service and Sales Workers

ISCO 6 - Skilled Agricultural, Forestry and Fishery Workers

Fig. 8 Word clouds by ISCO Major Groups (4–6). Additional word clouds following the same structure as in Fig. 7

Fig. 9 Word clouds by ISCO Major Groups (7–9). Additional word clouds following the same structure as in Fig. 7

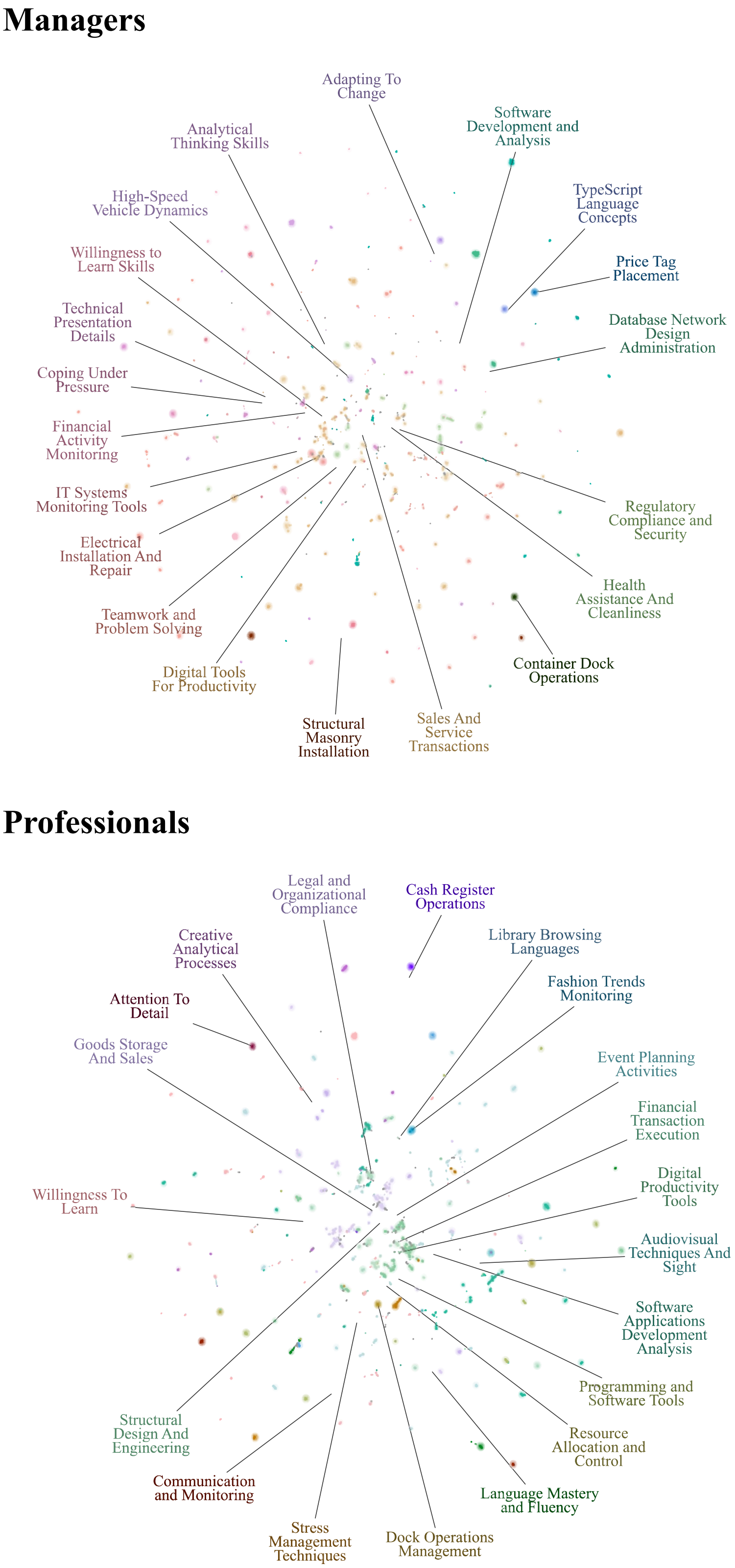


Fig. 10 Skills topics by ISCO Major Groups. Figure displays at maximum 20 identified topics from BERTopic model from a random sample of 1500 skills on average per major group. Topics are labeled based on 10 representative documents of each topic group using an API call to ChatGPT 4o with the following prompt 'I have a topic (Topic-{topic_number}) with the following keywords: {keywords}. Here are some representative documents for this topic: {docs[:10]}. Based on the above information, can you provide a concise and descriptive label for this topic in 4 words or less?' Source: Profesia data

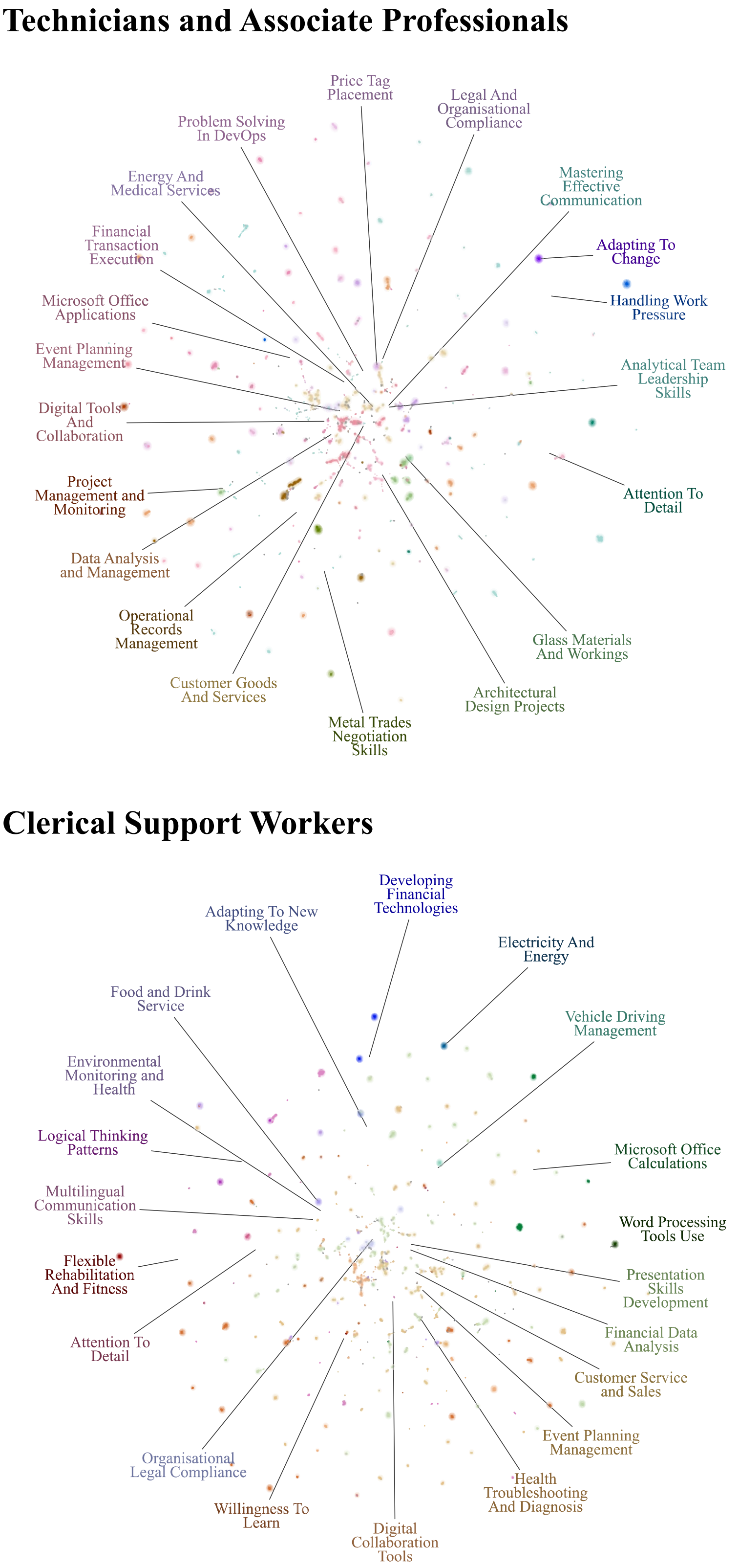


Fig. 11 Skills topics by ISCO Major Groups (continued). Additional skill topics following the same structure as in Fig. 10

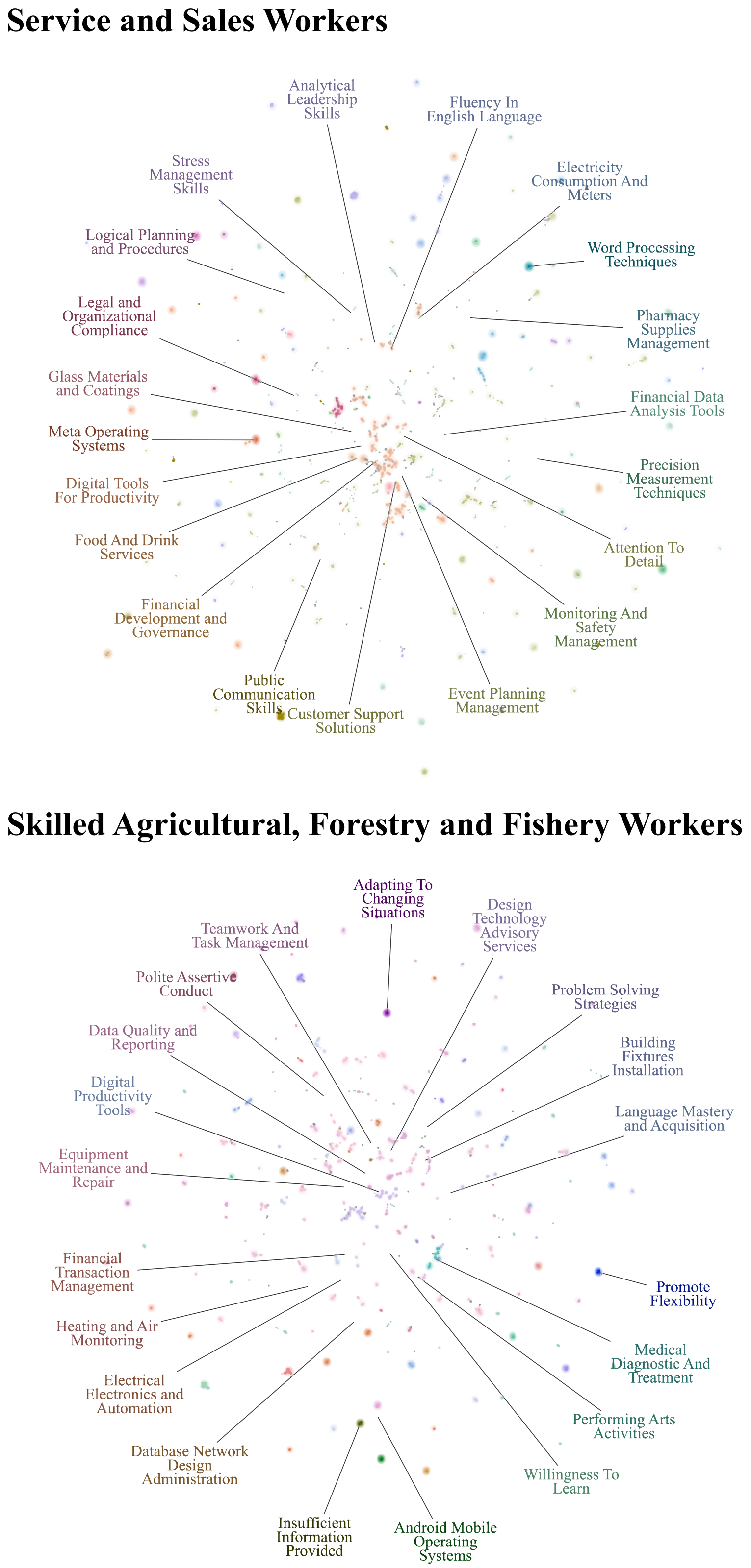


Fig. 12 Skills topics by ISCO Major Groups (continued). Additional skill topics following the same structure as in Fig. 10


Craft and Related Trades Workers

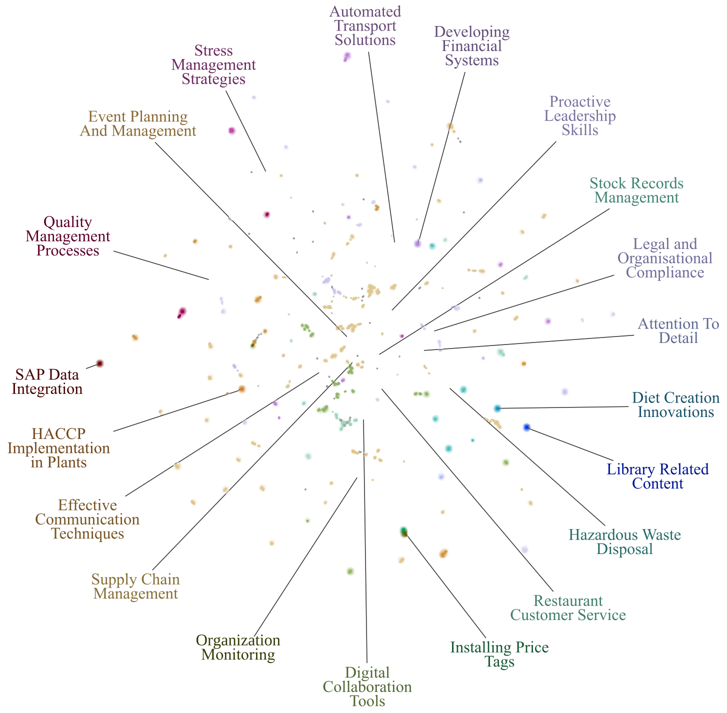

Plant and Machine Operators, and Assemblers

Fig. 13 Skills topics by ISCO Major Groups (continued). Additional skill topics following the same structure as in Fig. 10

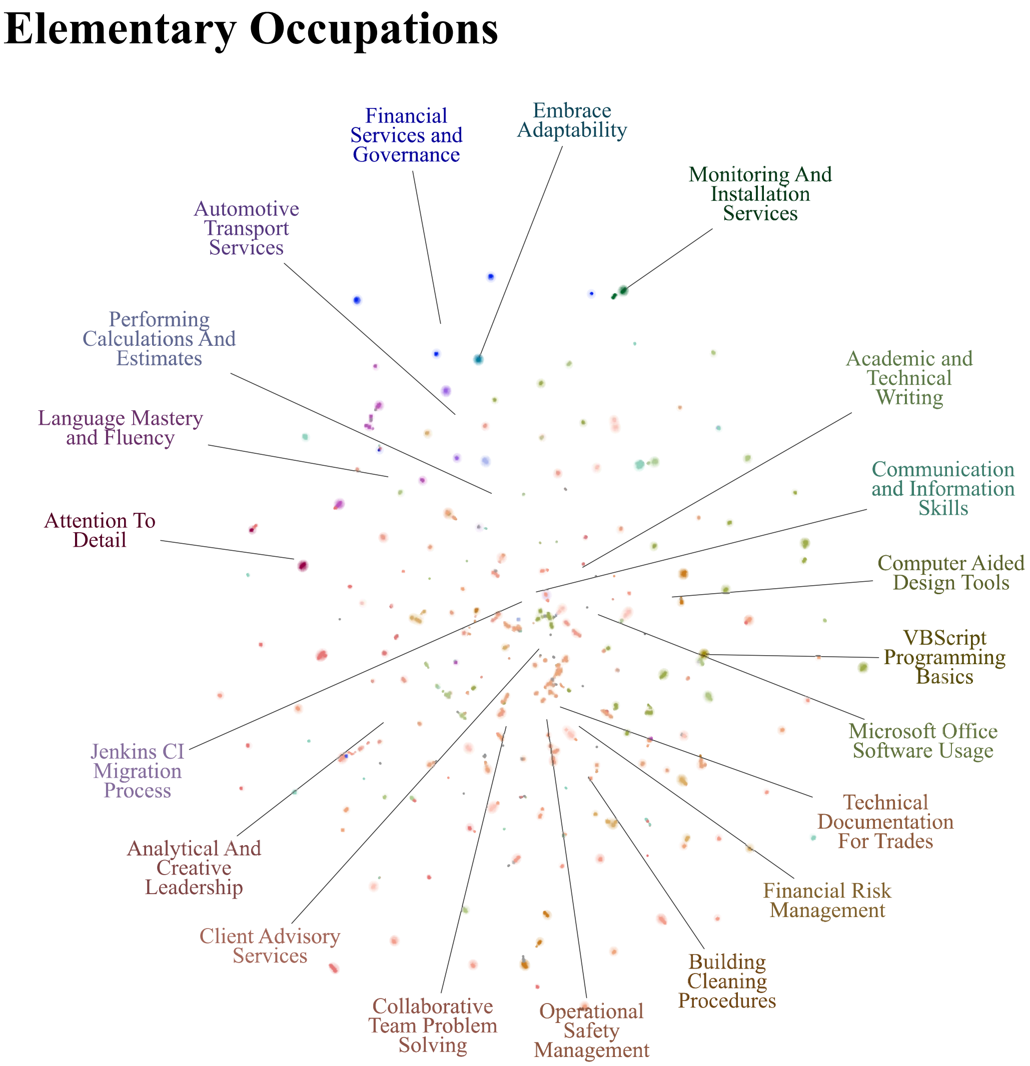


Fig. 14 Skills topics by ISCO Major Groups (continued). Additional skill topics following the same structure as in Fig. 10

Table 4 Summary statistics of wages, exposure to automation technologies and counts of conceptual skill categories

	Count	Mean	Std	Min	25%	50%	75%	Max
Log (monthly wage)	337903	7.10	0.40	−2.30	6.80	7.03	7.31	9.16
Robotics exposure	335734	0.19	1.01	−3.81	−0.41	0.21	1.05	1.65
Software exposure	335734	0.35	0.85	−3.41	0.08	0.34	0.97	1.63
AI and machine learning exposure	335734	0.27	0.86	−3.01	−0.01	0.40	0.89	1.70
Social skills	355845	0.65	1.12	0.00	0.00	0.00	1.00	20.00
Cognitive skills (narrow sense)	355845	1.83	2.65	0.00	0.00	1.00	2.00	35.00
Character skills	355845	0.44	0.85	0.00	0.00	0.00	1.00	13.00
Hand-foot-eye coordination skills	355845	0.54	0.89	0.00	0.00	0.00	1.00	10.00
Finger dexterity skills	355845	0.40	0.79	0.00	0.00	0.00	1.00	13.00
Software (specific) skills and technical support	355845	0.43	1.04	0.00	0.00	0.00	0.00	14.00
People management skills	355845	0.55	1.09	0.00	0.00	0.00	1.00	18.00
Writing skills	355845	0.08	0.31	0.00	0.00	0.00	0.00	8.00
Customer service skills	355845	0.27	0.65	0.00	0.00	0.00	0.00	11.00
Physical skills	355845	0.05	0.23	0.00	0.00	0.00	0.00	6.00
Financial skills	355845	0.12	0.41	0.00	0.00	0.00	0.00	9.00
Machine learning and AI skills	355845	0.06	0.34	0.00	0.00	0.00	0.00	9.00
Project management skills	355845	0.07	0.29	0.00	0.00	0.00	0.00	6.00
Language skills	355845	0.03	0.24	0.00	0.00	0.00	0.00	8.00
Computer (general) skills	355845	0.07	0.29	0.00	0.00	0.00	0.00	4.00

Source: Profesia data

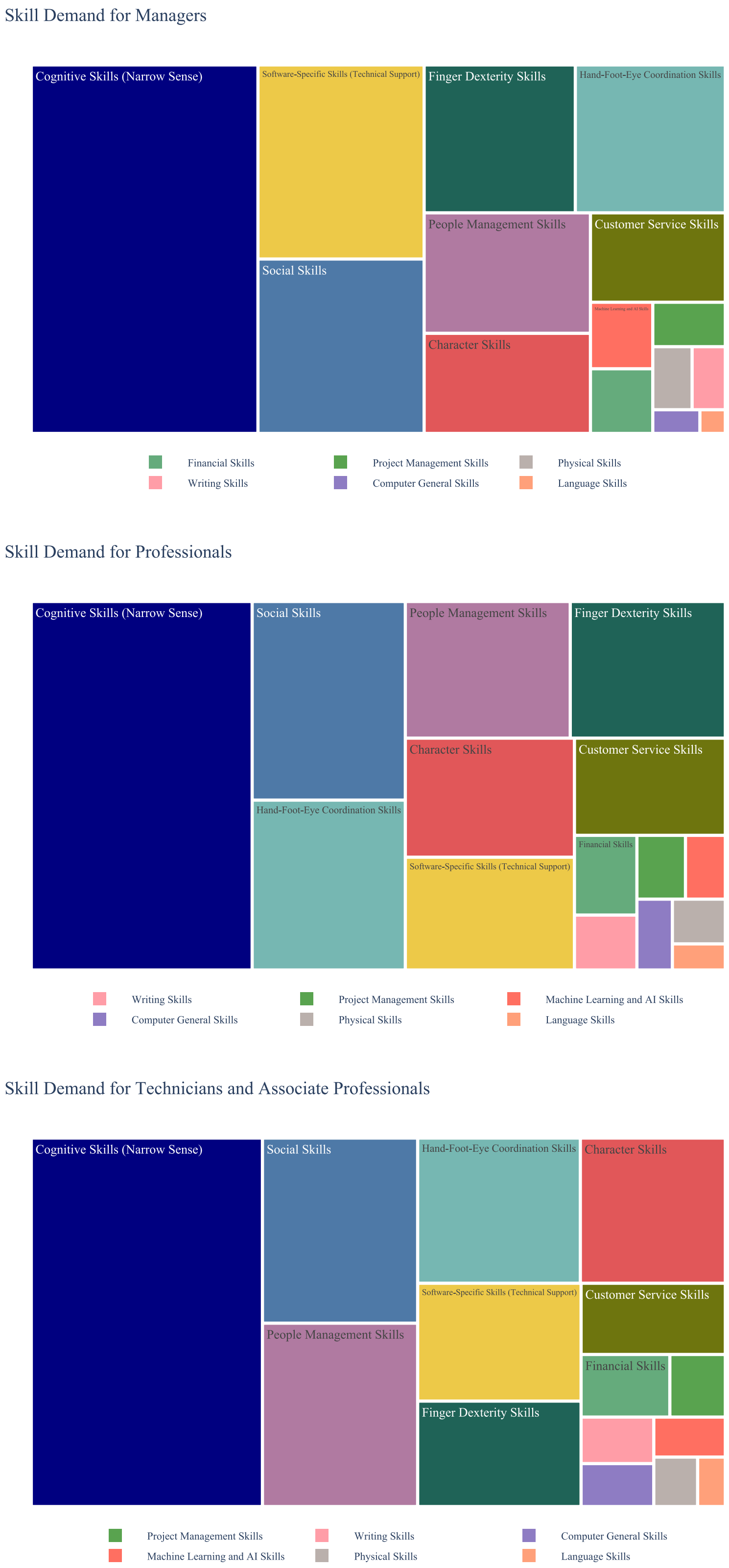


Fig. 15 Skill demand across ISCO Major Groups. The size of each rectangle represents the relative number of skills to the all skills within each ISCO major occupational group. Source: Profesia data

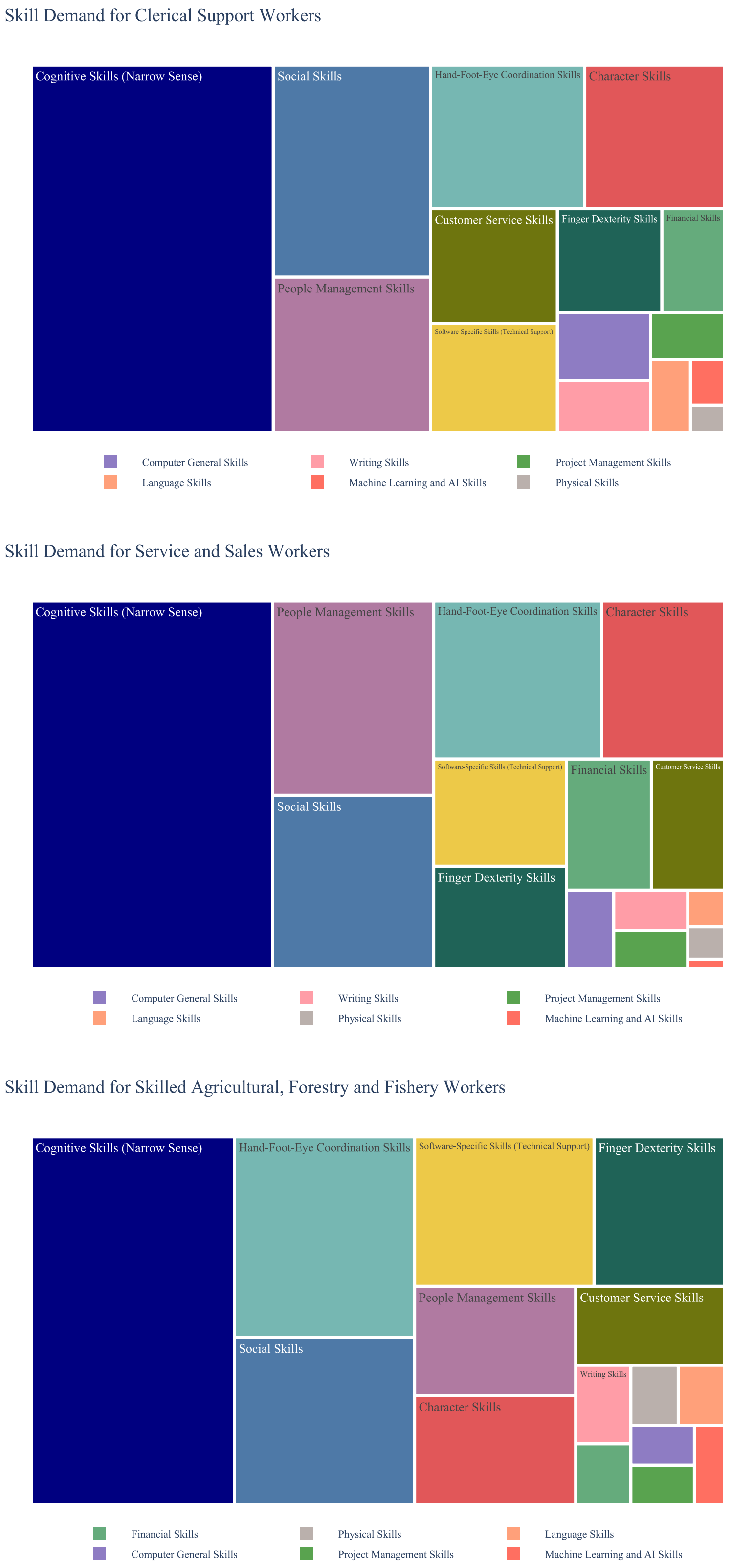
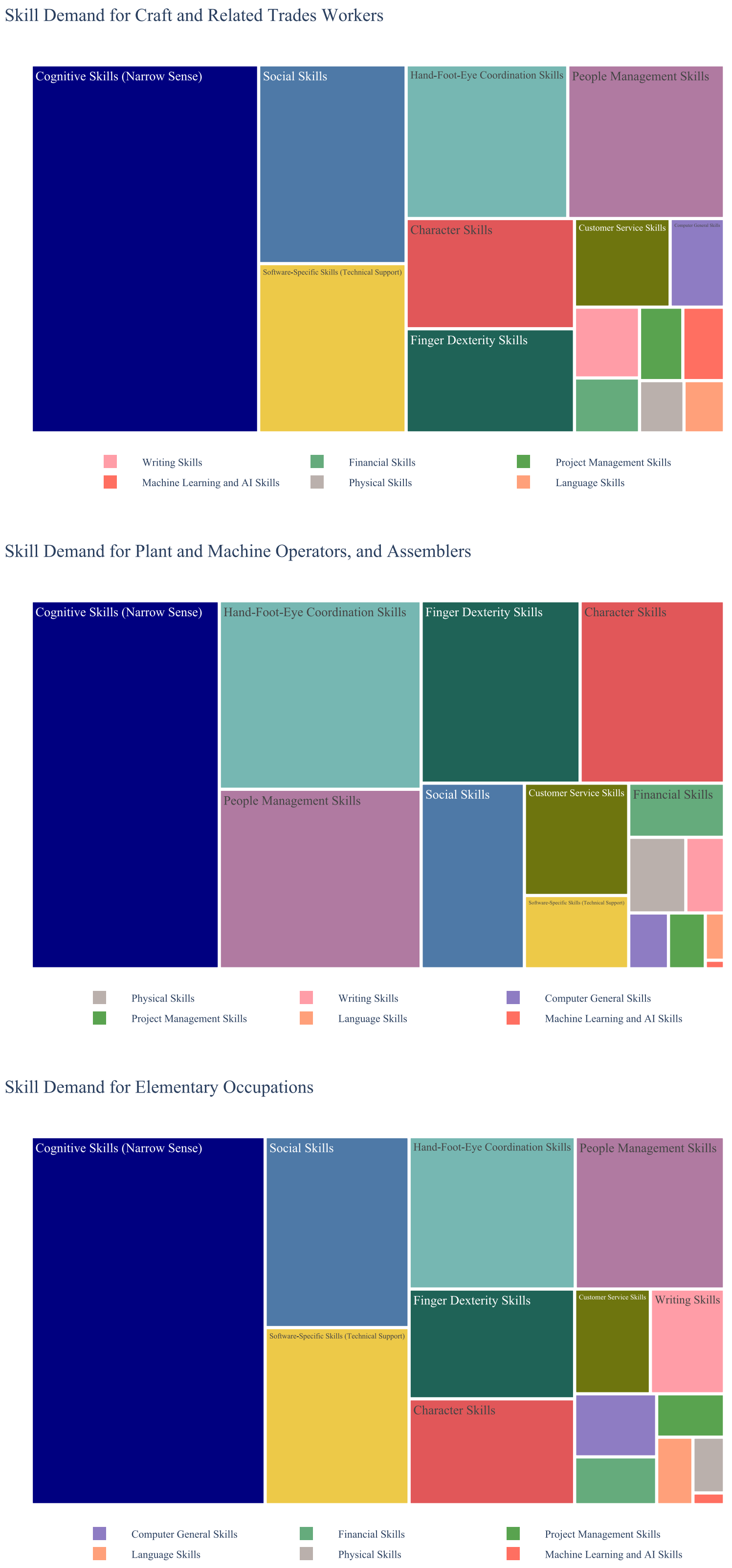


Fig. 16 Skill demand across ISCO Major Groups (continued). The size of each rectangle represents the relative number of skills to the all skills within each ISCO major occupational group. Source: Profesia data


Skill Demand for Craft and Related Trades Workers

Skill Demand for Plant and Machine Operators, and Assemblers

Skill Demand for Elementary Occupations

Fig. 17 Skill demand across ISCO Major Groups. The size of each rectangle represents the relative number of skills to the all skills within each ISCO major occupational group. Source: Profesia data

Table 5 Industry classification and aggregation to sectors base on NACE Rev. 2

Sector	Industries
Primary sector	A: Agriculture, Forestry and Fishing B: Mining and Quarrying
Secondary sector	C: Manufacturing D: Electricity, Gas, Steam and Air Conditioning Supply E: Water Supply; Sewerage, Waste Management and Remediation Activities F: Construction
Private services	G: Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles H: Transportation and Storage I: Accommodation and Food Service Activities J: Information and Communication K: Financial and Insurance Activities L: Real Estate Activities M: Professional, Scientific and Technical Activities N: Administrative and Support Service Activities R: Arts, Entertainment and Recreation S: Other Service Activities
Public & Social services	O: Public Administration and Defence; Compulsory Social Security P: Education Q: Human Health and Social Work Activities T: Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use U: Activities of Extraterritorial Organisations and Bodies

Table 6 Relationship between monthly wage and conceptual skill categories

	Log (monthly wage)							
	OLS	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Social skills	0.03** (0.00)	0.03** (0.00)	0.02* (0.01)	0.02* (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)
Cognitive skills (narrow sense)	0.03** (0.00)	0.03** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01* (0.00)	0.01** (0.00)	0.01* (0.00)	0.01** (0.00)
Character skills	0.02** (0.00)	0.02** (0.00)	0.01** (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)
Hand-foot-eye coordination skills	−0.01 (0.00)	−0.01 (0.01)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Finger dexterity skills	0.00 (0.01)	−0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)
Software-specific skills	0.06** (0.01)	0.05** (0.01)	0.01+ (0.00)	0.01+ (0.00)	0.01+ (0.00)	0.01+ (0.00)	0.01+ (0.00)	0.01+ (0.00)
People management skills	0.05** (0.01)	0.05** (0.01)	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)
Writing skills	0.03+ (0.01)	0.03+ (0.01)	0.02+ (0.01)	0.02+ (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Customer service skills	−0.00 (0.01)	−0.00 (0.01)	0.01 (0.01)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Physical skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	−0.00 (0.01)	0.00 (0.01)	−0.00 (0.01)	0.00 (0.01)
Financial skills	0.06** (0.01)	0.07** (0.01)	0.04** (0.01)	0.04** (0.01)	0.03** (0.00)	0.03** (0.01)	0.03** (0.00)	0.03** (0.01)
Machine Learning and AI skills	0.07* (0.02)	0.08** (0.01)	0.04** (0.00)	0.04** (0.00)	0.04** (0.00)	0.04** (0.00)	0.04** (0.00)	0.04** (0.00)
Project management skills	0.06* (0.01)	0.06* (0.01)	0.03+ (0.01)	0.03+ (0.01)	0.02+ (0.01)	0.02+ (0.01)	0.02+ (0.01)	0.02+ (0.01)
Language skills	0.00 (0.01)	0.01 (0.01)	0.02 (0.01)	0.02 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
Computer general skills	−0.05+ (0.02)	−0.05+ (0.02)	−0.02 (0.01)	−0.02 (0.01)	−0.03+ (0.01)	−0.03+ (0.01)	−0.03+ (0.01)	−0.03+ (0.01)
Constant	6.96** (0.05)	6.95** (0.04)	7.03** (0.00)	7.02** (0.00)	7.03** (0.00)	7.03** (0.00)	7.03** (0.00)	7.03** (0.00)
Broad occupational groups FE			✓	✓	✓	✓	✓	✓
Industries FE			✓	✓	✓	✓	✓	✓
Other controls					✓	✓	✓	✓
Month FE							✓	✓
N	337,895	337,895	336,822	336,822	326,553	326,553	326,553	326,553
Adj. R^2	0.25	0.25	0.44	0.44	0.63	0.63	0.63	0.64
R^2 within	0.25	0.25	0.06	0.06	0.05	0.05	0.05	0.05

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses

Table 7 Sector specific relationship between monthly wage and conceptual skill categories

	Log (monthly wage)							
	Primary sector		**Secondary sector**		**Private services**		**Public & Social services**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Social skills	0.06 (0.02)	0.03 (0.01)	0.03* (0.01)	0.01* (0.00)	0.02* (0.01)	0.01** (0.00)	0.01 (0.01)	0.02* (0.00)
Cognitive skills (narrow sense)	0.04+ (0.01)	0.03 (0.01)	0.01+ (0.00)	0.01+ (0.00)	0.01** (0.00)	0.01** (0.00)	−0.01 (0.01)	−0.01 (0.01)
Character skills	−0.02 (0.02)	−0.03 (0.02)	0.03* (0.01)	0.02* (0.01)	0.01* (0.00)	0.01+ (0.00)	0.00 (0.01)	0.00 (0.01)
Hand-foot-eye coordination skills	−0.01 (0.01)	−0.03+ (0.01)	0.00 (0.01)	0.01 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.02 (0.01)	−0.01 (0.01)
Finger dexterity skills	−0.03+ (0.01)	−0.02+ (0.01)	−0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01* (0.00)	0.02 (0.02)	0.03 (0.02)
Software-specific skills	−0.03 (0.02)	−0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01+ (0.00)	0.01+ (0.00)	−0.02 (0.02)	−0.00 (0.01)
People management skills	0.02 (0.02)	−0.00 (0.02)	0.02+ (0.01)	0.02** (0.00)	0.03** (0.00)	0.03** (0.00)	0.03+ (0.01)	0.03+ (0.01)
Writing skills	0.13 (0.12)	0.10 (0.06)	0.06+ (0.02)	0.04+ (0.02)	0.02 (0.01)	0.00 (0.01)	0.01 (0.03)	−0.02 (0.02)
Customer service skills	−0.01 (0.03)	−0.02 (0.04)	0.04 (0.02)	0.03 (0.01)	0.01 (0.01)	0.00 (0.00)	−0.01 (0.01)	−0.01 (0.01)
Physical skills	−0.05 (0.03)	0.00 (0.04)	−0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	−0.04 (0.10)	−0.04 (0.06)
Financial skills	−0.02 (0.05)	0.00 (0.07)	0.04+ (0.02)	0.04+ (0.01)	0.04** (0.01)	0.03** (0.01)	0.12 (0.07)	0.09 (0.04)
Machine Learning and AI skills	−0.18 (0.07)	−0.06 (0.06)	0.05 (0.05)	0.05 (0.03)	0.03** (0.01)	0.04** (0.00)	0.11+ (0.04)	0.07 (0.04)
Project management skills	0.02 (0.05)	−0.01 (0.04)	0.04+ (0.01)	0.01 (0.01)	0.03 (0.01)	0.02 (0.01)	0.01 (0.01)	0.00 (0.01)
Language skills	0.03 (0.12)	−0.07 (0.09)	0.14+ (0.05)	0.02 (0.02)	0.01 (0.01)	0.00 (0.01)	0.12 (0.08)	0.10 (0.04)
Computer general skills	0.09 (0.03)	0.04 (0.03)	0.01 (0.03)	0.00 (0.02)	−0.02 (0.01)	−0.03+ (0.01)	−0.03 (0.04)	−0.00 (0.03)
Constant	6.98** (0.01)	7.00** (0.01)	6.96** (0.01)	6.96** (0.00)	7.03** (0.01)	7.04** (0.00)	7.12** (0.01)	7.11** (0.01)
Broad occupational groups FE	✓	✓	✓	✓	✓	✓	✓	✓
Industries FE	✓	✓	✓	✓	✓	✓	✓	✓
Other controls		✓		✓		✓		✓
Month FE		✓		✓		✓		✓
N	1,044	1,032	66,114	65,914	259,294	249,223	10,138	10,058
Adj. R^2	0.17	0.51	0.32	0.69	0.47	0.64	0.25	0.56
R^2 within	0.04	0.02	0.03	0.03	0.08	0.05	0.02	0.03

All regressions are weighted with relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses. $**p < 0.001; *p < 0.01; +p < 0.05$

Table 8 Relationship between skill demand and firms highly exposed to automation technologies

	Skill demand														
	Social skills	**Cognitive skills**	**Character skills**	**Hand-foot-eye coordination skills**	**Finger dexterity skills**	**Software-specific skills**	**People management skills**	**Writing skills**	**Customer service skills**	**Physical skills**	**Financial skills**	**Machine learning and AI skills**	**Project management skills**	**Language skills**	**Computer general skills**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
AI and ML exposed firms	−0.002 (0.005)	0.165** (0.010)	0.052** (0.004)	0.014** (0.004)	0.051** (0.004)	0.019** (0.004)	0.038** (0.005)	0.001 (0.001)	0.018** (0.003)	0.006** (0.001)	0.017** (0.002)	0.002 (0.002)	0.005** (0.001)	−0.003* (0.001)	0.008** (0.001)
Constant	0.622** (0.002)	1.698** (0.004)	0.407** (0.002)	0.522** (0.002)	0.368** (0.002)	0.396** (0.002)	0.519** (0.002)	0.075** (0.001)	0.252** (0.001)	0.043** (0.001)	0.112** (0.001)	0.046** (0.001)	0.066** (0.001)	0.032** (0.001)	0.067** (0.001)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.243	0.444	0.179	0.131	0.144	0.345	0.251	0.095	0.174	0.052	0.155	0.163	0.098	0.087	0.126
Software exposed firms	0.084** (0.005)	0.286** (0.010)	0.052** (0.004)	0.048** (0.004)	0.008* (0.003)	0.063** (0.004)	0.066** (0.005)	−0.000 (0.001)	0.060** (0.003)	−0.001 (0.001)	−0.011** (0.002)	0.021** (0.002)	0.021** (0.001)	0.016** (0.001)	0.022** (0.001)
Constant	0.595** (0.002)	1.662** (0.004)	0.407** (0.002)	0.512** (0.002)	0.382** (0.002)	0.383** (0.002)	0.510** (0.002)	0.075** (0.001)	0.239** (0.001)	0.045** (0.000)	0.121** (0.001)	0.040** (0.001)	0.061** (0.001)	0.027** (0.000)	0.062** (0.001)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.243	0.445	0.179	0.131	0.143	0.345	0.251	0.095	0.176	0.052	0.155	0.164	0.099	0.088	0.127
Robotics exposed firms	−0.113** (0.005)	−0.141** (0.010)	−0.040** (0.004)	−0.026** (0.004)	−0.002 (0.003)	−0.041** (0.004)	−0.050** (0.005)	−0.003* (0.001)	−0.037** (0.003)	0.002 (0.001)	0.004* (0.002)	−0.017** (0.001)	−0.009** (0.001)	−0.011** (0.001)	−0.003* (0.001)
Constant	0.656** (0.002)	1.794** (0.004)	0.435** (0.002)	0.535** (0.002)	0.385** (0.002)	0.415** (0.002)	0.546** (0.002)	0.076** (0.001)	0.269** (0.001)	0.044** (0.001)	0.116** (0.001)	0.052** (0.001)	0.070** (0.001)	0.035** (0.001)	0.070** (0.001)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.244	0.443	0.179	0.131	0.143	0.345	0.251	0.095	0.175	0.052	0.155	0.163	0.098	0.087	0.126
N	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141

Table reports results for firms in the 70th percentile and above based on the distribution of labor demand exposure to AI and machine learning, software, robotics technology. The dependent variable is the count of in-demand skills by conceptual category. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Robust standard errors are in parentheses. $**p < 0.01; *p < 0.05; +p < 0.10$

Table 9 Relationship between skill demand and firms highly exposed to automation technologies

	Skills demand														
	Social skills	**Cognitive skills**	**Character skills**	**Hand-foot-eye coordination skills**	**Finger dexterity skills**	**Software-specific skills**	**People management skills**	**Writing skills**	**Customer service skills**	**Physical skills**	**Financial skills**	**Machine learning and AI skills**	**Project management skills**	**Language skills**	**Computer general skills**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
Panel A - 50th percentile															
AI and ML exposed firms	−0.019**	0.165**	0.027**	0.039** (0.004)	0.037**	0.045**	0.032**	0.005**	−0.002	0.007**	0.000	0.008**	0.008**	0.006**	0.017**
	(0.004)	(0.008)	(0.003)		(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.630**	1.669**	0.409**	0.508** (0.002)	0.366**	0.380**	0.514**	0.073**	0.259**	0.041**	0.117**	0.043**	0.063**	0.028**	0.061**
	(0.003)	(0.005)	(0.002)		(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.243	0.444	0.179	0.131	0.143	0.345	0.251	0.095	0.174	0.053	0.155	0.163	0.098	0.087	0.126
Software exposed firms	0.034**	0.188**	0.059**	0.020** (0.004)	0.047**	0.055**	0.062**	0.004**	0.032**	0.005**	0.002	0.001	0.012**	0.011**	0.015**
	(0.004)	(0.008)	(0.003)		(0.003)	(0.003)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
	(0.005)	(0.010)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.604**	1.657**	0.394**	0.517** (0.002)	0.361**	0.375**	0.499**	0.073**	0.242**	0.042**	0.117**	0.046**	0.061**	0.026**	0.062**
	(0.003)	(0.005)	(0.002)		(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.243	0.444	0.180	0.131	0.144	0.345	0.251	0.095	0.175	0.052	0.155	0.163	0.098	0.087	0.126
Robotics exposed firms	0.062**	0.220**	0.058**	0.069** (0.004)	0.049**	0.043**	0.061**	0.005**	0.015**	0.006**	0.006**	0.003*	0.014**	0.012**	0.022**
	(0.004)	(0.008)	(0.003)		(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.591**	1.641**	0.394**	0.493** (0.002)	0.360**	0.381**	0.500**	0.073**	0.250**	0.042**	0.114**	0.045**	0.060**	0.026**	0.058**
	(0.003)	(0.005)	(0.002)		(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.243	0.444	0.180	0.132	0.144	0.345	0.251	0.095	0.174	0.052	0.155	0.163	0.098	0.088	0.127
Panel B - 90th percentile															
AI and ML exposed firms	−0.088**	−0.184**	−0.099**	−0.086**	−0.069**	−0.051**	−0.108**	−0.030**	−0.003	−0.013**	−0.015**	−0.008**	−0.005**	−0.006**	−0.007**
	(0.005)	(0.010)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.631**	1.771**	0.434**	0.537** (0.002)	0.392**	0.408**	0.542**	0.078**	0.258**	0.046**	0.119**	0.047**	0.068**	0.032**	0.070**
	(0.002)	(0.004)	(0.001)		(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
R^2	0.243	0.444	0.179	0.131	0.144	0.345	0.251	0.095	0.174	0.052	0.155	0.163	0.098	0.087	0.126
Software exposed firms	−0.017**	0.057**	−0.021**	−0.050**	−0.042**	−0.033**	−0.040**	−0.021**	0.026**	−0.005**	0.002	0.002	0.002	−0.007**	−0.015**
	(0.006)	(0.015)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	0.623**	1.744**	0.425**	0.533** (0.002)	0.389**	0.406**	0.535**	0.077**	0.255**	0.045**	0.117**	0.046**	0.067**	0.032**	0.071**
	(0.002)	(0.003)	(0.001)		(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
R^2	0.243	0.443	0.179	0.131	0.143	0.345	0.251	0.096	0.174	0.052	0.155	0.163	0.098	0.087	0.126
Robotics exposed firms	−0.088**	−0.240**	−0.097**	−0.079**	−0.075**	−0.058**	−0.135**	−0.026**	0.000	−0.014**	−0.014**	−0.010**	−0.007**	−0.006**	−0.004**
	(0.005)	(0.010)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.631**	1.777**	0.434**	0.536** (0.002)	0.393**	0.408**	0.545**	0.078**	0.258**	0.046**	0.119**	0.048**	0.068**	0.032**	0.069**
	(0.002)	(0.004)	(0.001)		(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 9 (continued)

	Skills demand														
	Social skills	**Cognitive skills**	**Character skills**	**Hand-foot-eye coordination skills**	**Finger dexterity skills**	**Software-specific skills**	**People management skills**	**Writing skills**	**Customer service skills**	**Physical skills**	**Financial skills**	**Machine learning and AI skills**	**Project management skills**	**Language skills**	**Computer general skills**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
R^2	0.243	0.444	0.180	0.131	0.144	0.345	0.252	0.096	0.174	0.053	0.155	0.163	0.098	0.087	0.126
N	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141	344,141

Panel A reports results for firms in the 50th percentile and above, and Panel B for those in the 90th percentile and above, based on the distribution of labor demand exposure to AI, machine learning, software, and robotics. The dependent variable is the count of in-demand skills by conceptual category. Controls include region of work, workplace type, temporary work agencies, type of contract, and minimum education level. Robust standard errors are in parentheses. $**p < 0.01; *p < 0.05; +p < 0.10$

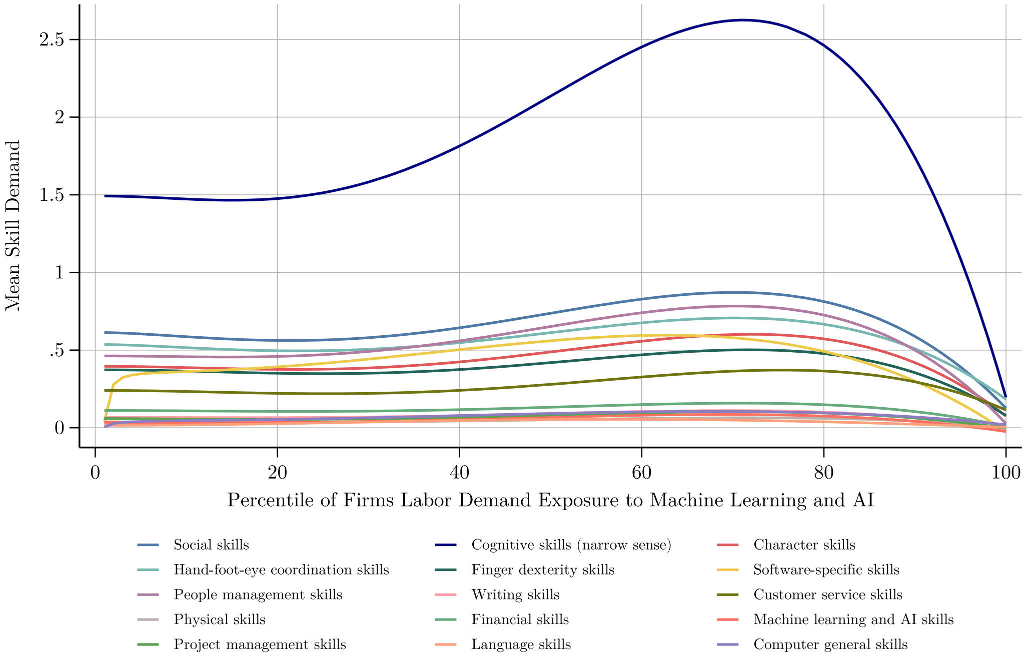


Fig. 18 Unconditional mean skill demand across firms labor demand exposure to AI and machine learning technology

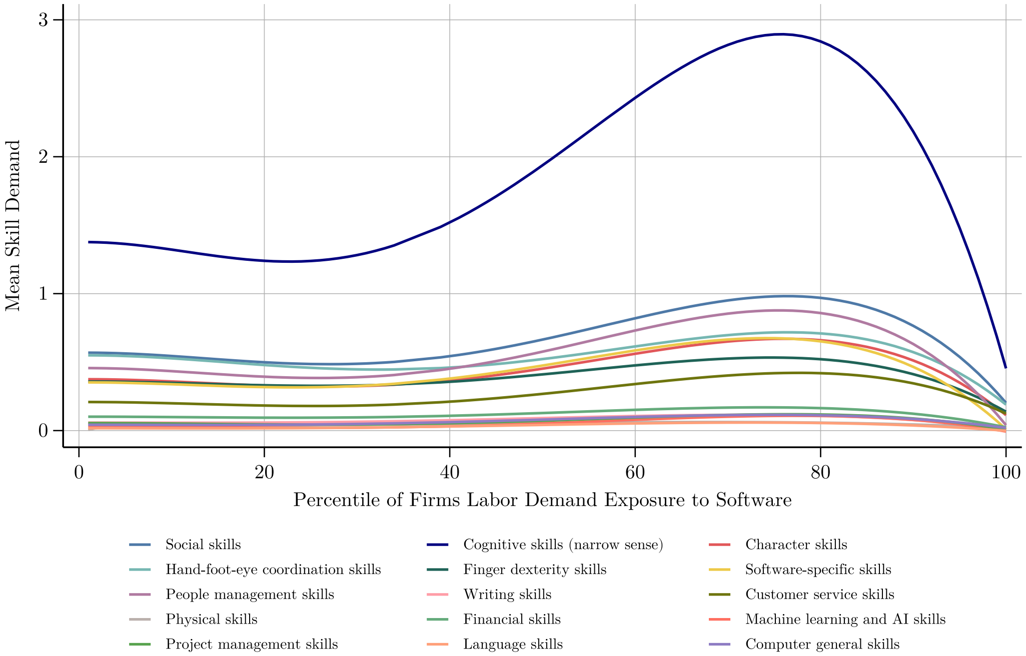


Fig. 19 Unconditional mean skill demand across firms labor demand exposure to software technology

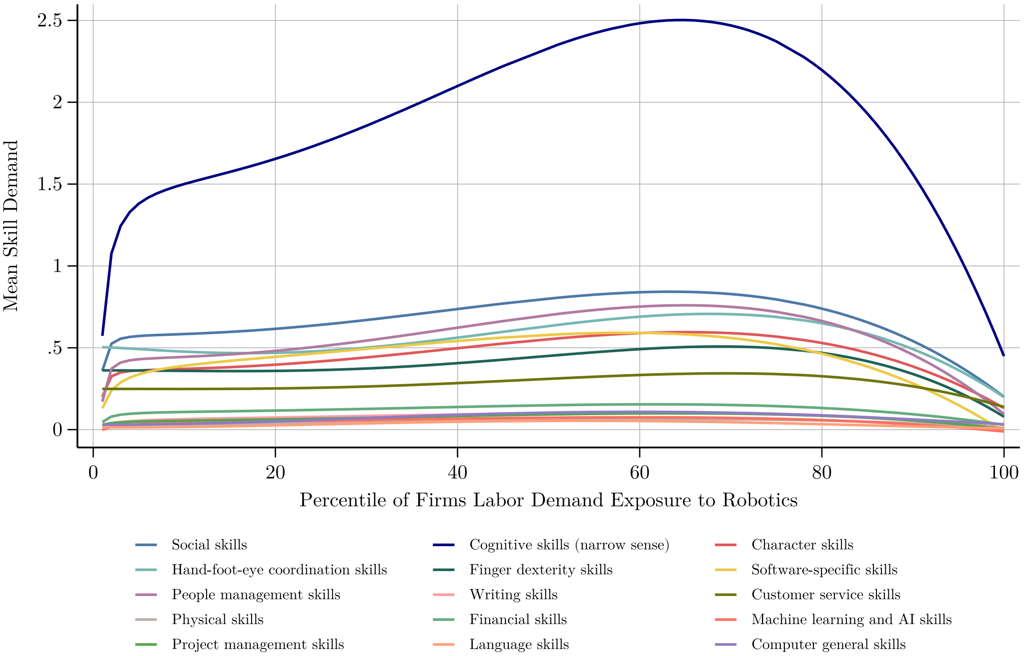


Fig. 20 Unconditional mean skill demand across firms labor demand exposure to robotics technology

Table 10 Relationship between exposure to AI and machine learning and conceptual skill categories

	Exposure to AI and machine learning					
	OLS	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Social skills	0.01 (0.00)	0.01+ (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Cognitive skills (narrow sense)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Character skills	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Hand-foot-eye coordination skills	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)
Finger dexterity skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Software-specific skills	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
People management skills	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.00 (0.00)	−0.01 (0.01)	−0.00 (0.00)
Writing skills	0.00 (0.02)	−0.01 (0.01)	−0.00 (0.02)	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)
Customer service skills	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Physical skills	0.01 (0.01)	0.01 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)
Financial skills	−0.02 (0.02)	−0.01 (0.02)	−0.02 (0.02)	−0.02 (0.02)	−0.02 (0.02)	−0.02 (0.02)
Machine learning and AI skills	−0.03+ (0.02)	−0.04* (0.02)	−0.04+ (0.02)	−0.05* (0.02)	−0.04* (0.02)	−0.05* (0.02)
Project management skills	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)
Language skills	0.03+ (0.01)	0.03* (0.01)	0.03+ (0.01)	0.03* (0.01)	0.03+ (0.01)	0.03* (0.01)
Computer general skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Broad occupational groups FE	✓	✓	✓	✓	✓	✓
Industries FE	✓	✓	✓	✓	✓	✓
Other controls			✓	✓	✓	✓
Months FE					✓	✓
N	334,677	334,677	324,246	324,246	324,246	324,246
Adj. R2	0.55	0.49	0.55	0.50	0.55	0.50

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses

Table 11 Relationship between exposure to software and conceptual skill categories

	Exposure to software					
	OLS	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Social skills	0.01 (0.00)	0.01+ (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)
Cognitive skills (narrow sense)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Character skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Hand-foot-eye coordination skills	−0.01** (0.00)	−0.01** (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)
Finger dexterity skills	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
Software-specific skills	−0.00 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
People management skills	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
Writing skills	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	−0.00 (0.01)	0.01 (0.01)	−0.00 (0.01)
Customer service skills	0.02 (0.01)	0.02* (0.01)	0.01 (0.01)	0.02+ (0.01)	0.01 (0.01)	0.02+ (0.01)
Physical skills	0.02 (0.01)	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Financial skills	−0.01 (0.02)	−0.01 (0.01)	−0.01 (0.02)	−0.01 (0.01)	−0.01 (0.02)	−0.01 (0.01)
Machine Learning and Artificial Intelligence	−0.03 (0.02)	−0.04* (0.02)	−0.03 (0.02)	−0.04* (0.02)	−0.03 (0.02)	−0.04* (0.02)
Project management skills	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Language skills	0.03+ (0.02)	0.04* (0.02)	0.04+ (0.02)	0.04* (0.02)	0.04+ (0.02)	0.04* (0.02)
Computer general skills	0.00 (0.02)	0.01 (0.02)	−0.00 (0.01)	0.00 (0.02)	−0.00 (0.01)	0.00 (0.02)
Broad occupational groups FE	✓	✓	✓	✓	✓	✓
Industries FE	✓	✓	✓	✓	✓	✓
Other controls			✓	✓	✓	✓
Months FE					✓	✓
N	334,677	334,677	324,246	324,246	324,246	324,246
Adj. R2	0.48	0.45	0.48	0.45	0.48	0.45

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses. $**p < 0.01; *p < 0.05; +p < 0.10$

Table 12 Relationship between exposure to robotics and conceptual skill categories

	Exposure to robotics					
	OLS	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Social skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)
Cognitive skills (narrow sense)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.01 (0.00)	−0.00 (0.00)	−0.01 (0.00)
Character skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Hand-foot-eye coordination skills	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (0.00)
Finger dexterity skills	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Software-specific skills	−0.02* (0.01)	−0.02* (0.01)	−0.02* (0.01)	−0.02* (0.01)	−0.02* (0.01)	−0.02* (0.01)
People management skills	−0.00 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.00 (0.01)
Writing skills	0.00 (0.02)	0.00 (0.02)	0.01 (0.02)	0.00 (0.02)	0.01 (0.02)	0.00 (0.02)
Customer service skills	0.01 (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Physical skills	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Financial skills	−0.02 (0.03)	−0.02 (0.03)	−0.02 (0.03)	−0.02 (0.02)	−0.02 (0.03)	−0.02 (0.02)
Machine learning and artificial intelligence	−0.04 (0.03)	−0.06 (0.03)	−0.05+ (0.03)	−0.07+ (0.03)	−0.05+ (0.03)	−0.07+ (0.03)
Project management skills	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Language skills	0.03 (0.02)	0.03+ (0.02)	0.03 (0.02)	0.04+ (0.02)	0.03 (0.02)	0.04+ (0.02)
Computer general skills	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Broad occupational groups FE	✓	✓	✓	✓	✓	✓
Industries FE	✓	✓	✓	✓	✓	✓
Other controls			✓	✓	✓	✓
Months FE					✓	✓
N	334,677	334,677	324,246	324,246	324,246	324,246
Adj. R2	0.49	0.44	0.49	0.44	0.49	0.44

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses

$**p < 0.01; *p < 0.05; +p < 0.10$

Table 13 Sector specific relationship between exposure to AI and machine learning, software, robotics technology and conceptual skill categories

	Primary & Secondary sector			**Private services**			**Public & Social services**		
	AI and ML	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Social skills	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.01 (0.00)	0.01+ (0.00)	0.04 (0.02)	0.04 (0.02)	0.05 (0.03)
Cognitive skills (narrow sense)	0.00 (0.01)	−0.00 (0.02)	0.00 (0.01)	−0.00 (0.00)	−0.00 (0.00)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01+ (0.00)
Character skills	0.01 (0.01)	0.01 (0.01)	0.02+ (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.02)	0.00 (0.02)	0.02 (0.02)
Hand-foot-eye coordination skills	0.01 (0.01)	0.01 (0.01)	0.00 (0.02)	−0.01** (0.00)	−0.02* (0.00)	−0.01* (0.00)	0.02 (0.01)	0.02 (0.01)	0.02 (0.02)
Finger dexterity skills	0.01 (0.00)	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.02 (0.02)	−0.08* (0.02)	−0.07+ (0.02)	−0.12* (0.03)
Software-specific skills	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.02+ (0.01)	−0.18 (0.15)	−0.19 (0.14)	−0.27 (0.18)
People management skills	0.03+ (0.01)	0.03 (0.01)	0.04+ (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	0.01 (0.01)	−0.00 (0.01)	−0.00 (0.01)
Writing skills	0.02 (0.02)	0.02 (0.02)	0.03 (0.01)	−0.02 (0.01)	−0.01 (0.01)	−0.01 (0.01)	0.02 (0.03)	0.03 (0.02)	−0.02 (0.05)
Customer service skills	0.00 (0.02)	0.02 (0.03)	0.01 (0.03)	0.01 (0.01)	0.02* (0.00)	0.01 (0.01)	0.08 (0.08)	0.06 (0.08)	0.07 (0.09)
Physical skills	0.02 (0.02)	0.03 (0.02)	0.03 (0.03)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	−0.28+ (0.09)	−0.24+ (0.08)	−0.40+ (0.11)
Financial skills	−0.05 (0.03)	−0.05 (0.04)	−0.02 (0.02)	−0.01 (0.02)	−0.01 (0.01)	−0.02 (0.02)	−0.06+ (0.02)	−0.05 (0.03)	−0.01 (0.02)
Machine learning and AI skills	0.08 (0.05)	0.12 (0.06)	0.09 (0.05)	−0.05 (0.03)	−0.04 (0.03)	−0.07 (0.04)	−0.07 (0.05)	−0.06 (0.05)	−0.01 (0.09)
Project management skills	−0.07+ (0.03)	−0.09* (0.03)	−0.08 (0.05)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	−0.09** (0.01)	−0.07* (0.01)	−0.07+ (0.02)
Language skills	−0.05 (0.08)	−0.07 (0.10)	−0.03 (0.08)	0.04* (0.01)	0.05* (0.01)	0.05+ (0.02)	0.02 (0.02)	0.02 (0.02)	−0.01 (0.04)
Computer general skills	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)	0.00 (0.01)	−0.00 (0.01)	0.01 (0.02)	0.12 (0.06)	0.12 (0.06)	0.18 (0.08)
Constant	0.16** (0.01)	0.17** (0.01)	0.06** (0.01)	0.40** (0.01)	0.46** (0.01)	0.33** (0.01)	0.50** (0.02)	0.55** (0.02)	0.53** (0.02)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	63,008	63,008	63,008	246,625	246,625	246,625	14,305	14,305	14,305
Adj. R^2	0.55	0.54	0.53	0.49	0.44	0.43	0.61	0.54	0.55

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups are in parentheses. $**p < 0.01; *p < 0.05; +p < 0.10$

Table 14 Relationship between exposure to AI and machine learning, software, robotics technology and conceptual skill categories

	Exposure to AI and ML		**Exposure to software**		**Exposure to robotics**	
	OLS	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Social skills	0.00 (0.01)	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
Cognitive skills (narrow sense)	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)
Character skills	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Hand-foot-eye coordination skills	−0.01 (0.01)	−0.01 (0.01)	−0.01* (0.01)	−0.01* (0.01)	−0.01 (0.01)	−0.01+ (0.01)
Finger dexterity skills	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)
Software-specific skills	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.02** (0.01)	−0.02** (0.01)
People management skills	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.02)	−0.00 (0.01)
Writing skills	0.01 (0.02)	0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.03 (0.03)	0.03 (0.02)
Customer service skills	0.02 (0.02)	0.02 (0.01)	0.02 (0.02)	0.03* (0.01)	0.01 (0.02)	0.02 (0.02)
Physical skill	−0.02 (0.01)	−0.02 (0.01)	−0.02 (0.02)	−0.02 (0.02)	−0.02 (0.02)	−0.02 (0.02)
Financial skills	−0.04+ (0.02)	−0.04+ (0.02)	−0.04+ (0.02)	−0.04* (0.02)	−0.05 (0.03)	−0.05+ (0.02)
Machine Learning and AI skills	−0.05* (0.02)	−0.06** (0.02)	−0.03 (0.02)	−0.05* (0.02)	−0.09* (0.03)	−0.11** (0.03)
Project management skills	−0.01 (0.02)	−0.02 (0.02)	−0.00 (0.02)	−0.00 (0.02)	−0.01 (0.02)	−0.01 (0.02)
Language skills	0.04+ (0.02)	0.04* (0.02)	0.04* (0.02)	0.04+ (0.02)	0.05+ (0.02)	0.05* (0.02)
Computer general skills	0.01 (0.01)	0.01 (0.01)	−0.00 (0.01)	0.00 (0.02)	0.02 (0.01)	0.02 (0.02)
Cognitive skills (narrow sense) × Social skills	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Character skills × Social skills	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Hand-foot-eye coordination skills × Social skills	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Finger dexterity skills × Social skills	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.01 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Software-specific skills × Social skills	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
People management skills × Social skills	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Writing skills × Social skills	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.02+ (0.01)	−0.01+ (0.01)
Customer service skills × Social skills	−0.01 (0.00)	−0.01+ (0.00)	−0.01 (0.00)	−0.01+ (0.00)	−0.01 (0.01)	−0.01 (0.00)
Physical skills × Social skills	0.02** (0.00)	0.02** (0.00)	0.02** (0.01)	0.02** (0.01)	0.02 (0.01)	0.02+ (0.01)
Financial skills × Social skills	0.02** (0.00)	0.02** (0.00)	0.02** (0.00)	0.02** (0.00)	0.02** (0.01)	0.02** (0.00)
Machine Learning and AI skills × Social skills	0.00 (0.00)	0.01+ (0.00)	0.00 (0.00)	0.01+ (0.00)	0.01* (0.01)	0.02** (0.00)
Project management skills × Social skills	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Language skills × Social skills	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.01)	0.00 (0.00)	−0.01 (0.01)	−0.01 (0.01)
Computer general skills × Social skills	−0.00 (0.01)	−0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)
Constant	0.28** (0.00)	0.36** (0.00)	0.35** (0.00)	0.40** (0.00)	0.20** (0.00)	0.29** (0.00)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓
N	324,246	324,246	324,246	324,246	324,246	324,246
Adj. R2	0.55	0.50	0.48	0.45	0.49	0.44

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups and industries are in parentheses

$**p < 0.01; *p < 0.05; +p < 0.10$

Table 15 Sector specific relationship between exposure to AI and machine learning, software, robotics technology and conceptual skill categories

	Primary & Secondary Sector			**Private Services**			**Public & Social Services**		
	AI and ML	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Social skills	0.04 (0.03)	0.04 (0.03)	0.05 (0.03)	−0.01 (0.00)	−0.00 (0.01)	−0.01 (0.01)	0.03 (0.03)	0.05 (0.03)	0.05 (0.05)
Cognitive skills (narrow sense)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	−0.00 (0.00)	−0.00 (0.00)	−0.01 (0.00)	0.00 (0.01)	−0.00 (0.00)	−0.01 (0.01)
Character skills	0.02* (0.01)	0.01 (0.01)	0.03** (0.01)	0.01* (0.00)	0.01* (0.00)	0.01 (0.01)	0.01 (0.03)	0.02 (0.03)	0.03 (0.04)
Hand-foot-eye coordination skills	−0.02 (0.01)	−0.03+ (0.01)	−0.03** (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	0.01 (0.03)	0.03 (0.03)	0.02 (0.05)
Finger dexterity skills	−0.00 (0.02)	−0.00 (0.02)	−0.01 (0.03)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.06)	0.03 (0.07)	0.03 (0.09)
Software-specific skills	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	−0.01 (0.01)	−0.00 (0.02)	−0.02 (0.02)	−0.13 (0.13)	−0.14 (0.12)	−0.21 (0.15)
People management skills	0.04* (0.01)	0.05* (0.02)	0.06** (0.02)	−0.02* (0.01)	−0.02* (0.01)	−0.01 (0.01)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Writing skills	0.09 (0.05)	0.11+ (0.05)	0.07* (0.03)	−0.01 (0.03)	−0.01 (0.02)	0.01 (0.02)	−0.02 (0.10)	0.01 (0.11)	−0.04 (0.09)
Customer service skills	0.03 (0.05)	0.04 (0.06)	0.04 (0.07)	0.02 (0.01)	0.02+ (0.01)	0.01 (0.02)	0.12 (0.07)	0.10 (0.07)	0.12 (0.11)
Physical skills	−0.03 (0.05)	−0.01 (0.04)	0.01 (0.04)	−0.04** (0.01)	−0.04* (0.01)	−0.04* (0.02)	−0.14 (0.30)	−0.14 (0.31)	−0.35 (0.40)
Financial skills	−0.17+ (0.08)	−0.20 (0.11)	−0.14+ (0.07)	−0.05* (0.02)	−0.05* (0.02)	−0.06** (0.02)	−0.33** (0.07)	−0.33** (0.07)	−0.22 (0.12)
Machine learning and AI skills	0.13* (0.05)	0.12 (0.07)	0.17* (0.06)	−0.04 (0.03)	−0.03 (0.03)	−0.07 (0.05)	−0.14 (0.27)	−0.16 (0.27)	−0.40 (0.25)
Project management skills	−0.03 (0.05)	−0.05 (0.06)	−0.01 (0.04)	0.03* (0.01)	0.02 (0.02)	0.04 (0.02)	−0.10+ (0.05)	−0.05 (0.06)	−0.03 (0.11)
Language skills	−0.15 (0.09)	−0.18 (0.11)	−0.14 (0.09)	0.03* (0.01)	0.03+ (0.01)	0.03+ (0.02)	−0.06 (0.05)	−0.04 (0.05)	−0.09 (0.06)
Computer general skills	−0.03 (0.07)	−0.06 (0.07)	−0.05 (0.08)	0.02 (0.02)	0.01 (0.02)	0.03 (0.02)	0.08 (0.13)	0.09 (0.12)	0.15 (0.18)
Cognitive skills (narrow sense) × Social skills	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.01 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Character skills × Social skills	−0.01+ (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.00 (0.00)	−0.00+ (0.00)	−0.00 (0.00)	−0.00 (0.01)	−0.01 (0.00)	−0.02+ (0.01)
Hand-foot-eye coordination skills × Social	0.02 (0.01)	0.03 (0.02)	0.02 (0.01)	−0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.01)	−0.00 (0.01)	0.00 (0.02)
Finger dexterity skills × Social skills	0.00 (0.01)	−0.00 (0.01)	0.00 (0.01)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.02)	−0.01 (0.02)	−0.00 (0.02)
Software-specific skills × Social	−0.00 (0.01)	−0.00 (0.01)	0.00 (0.01)	0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)
People management skills × Social skills	−0.02* (0.01)	−0.02* (0.01)	−0.02* (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.01)	0.00 (0.01)	−0.00 (0.01)
Writing skills × Social skills	−0.04+ (0.02)	−0.05* (0.02)	−0.03* (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.01+ (0.01)	0.01 (0.02)	0.00 (0.02)	0.00 (0.01)
Customer service skills × Social skills	−0.01 (0.01)	−0.01 (0.01)	−0.02 (0.02)	−0.00 (0.00)	−0.01 (0.00)	−0.00 (0.00)	−0.01+ (0.01)	−0.02* (0.01)	−0.02* (0.01)
Physical skills × Social skills	0.02 (0.01)	0.02 (0.02)	0.01 (0.02)	0.02** (0.01)	0.03** (0.01)	0.02+ (0.01)	−0.01 (0.09)	0.01 (0.09)	0.02 (0.13)
Financial skills × Social skills	0.05 (0.04)	0.06 (0.05)	0.06 (0.04)	0.02** (0.01)	0.02** (0.01)	0.02** (0.00)	0.09* (0.04)	0.09+ (0.04)	0.07 (0.06)
Machine Learning and AI skills × Social skills	−0.03 (0.03)	−0.01 (0.04)	−0.04 (0.02)	0.00 (0.00)	0.00 (0.00)	0.01 (0.01)	0.06* (0.02)	0.06+ (0.03)	0.10+ (0.05)
Project management skills × Social skills	0.01 (0.03)	0.02 (0.03)	0.01 (0.02)	−0.01 (0.01)	−0.00 (0.01)	−0.01 (0.01)	0.00 (0.01)	−0.00 (0.02)	−0.02 (0.04)

Table 15 (continued)

	Primary & Secondary Sector			Private Services			Public & Social Services		
	AI and ML	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**	**AI and ML**	**Software**	**Robotics**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Language skills × Social skills	0.08+ (0.03)	0.10+ (0.05)	0.07* (0.03)	−0.00 (0.00)	0.00 (0.00)	−0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Computer general skills × Social skills	0.02 (0.03)	0.03 (0.03)	0.01 (0.03)	−0.00 (0.00)	−0.00 (0.00)	−0.01 (0.01)	−0.00 (0.04)	−0.01 (0.05)	−0.03 (0.07)
Constant	0.11+ (0.05)	0.12+ (0.06)	0.08 (0.04)	0.31** (0.01)	0.44** (0.02)	0.24** (0.02)	0.16+ (0.07)	0.25** (0.06)	0.14 (0.10)
Broad occupational groups, Industries, Month FE and Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	14,657	14,657	14,657	98,827	98,827	98,827	4,674	4,674	4,674
Adj. R^2	0.55	0.52	0.57	0.55	0.48	0.48	0.67	0.58	0.64

Weights are relative employment share of ISCO-08 major groups in year 2020 sourced from Statistical Office of Slovakia. Controls include: region of work, workplace type, temporary work agencies, type of contract and minimal education level. Standard errors clustered at the level of broad occupational groups are in parentheses.$**p < 0.01; *p < 0.05; +p < 0.10$

Table 16 Average treatment effects of skill presence on automation exposure to technology τ

	$\mathbf{ATE}^{\text{AI and ML}}$	$\mathbf{ATE}^{\text{Software}}$	$\mathbf{ATE}^{\text{Robotics}}$
Social skills	0.015** (0.003)	0.022** (0.003)	0.007* (0.003)
Cognitive skills (narrow sense)	0.002 (0.003)	0.005 (0.003)	−0.015** (0.004)
Character skills	0.008** (0.003)	0.017** (0.003)	0.017** (0.003)
Hand-foot-eye coordination skills	−0.022** (0.002)	−0.029** (0.003)	−0.022** (0.003)
Finger dexterity skills	0.008** (0.003)	0.011** (0.003)	0.014** (0.003)
Software-specific skills	−0.058** (0.006)	−0.047** (0.006)	−0.082** (0.007)
People management skills	−0.029** (0.004)	−0.014** (0.004)	−0.038** (0.004)
Writing skills	−0.044* (0.016)	−0.012 (0.017)	−0.015 (0.018)
Customer service skills	0.033** (0.004)	0.048** (0.004)	0.043** (0.005)
Physical skills	−0.032+ (0.017)	−0.032+ (0.019)	−0.030 (0.022)
Financial skills	−0.070** (0.009)	−0.065** (0.010)	−0.086** (0.011)
Machine Learning and AI skills	0.006 (0.044)	−0.021 (0.042)	0.001 (0.051)
Project management skills	−0.028* (0.009)	−0.010 (0.010)	−0.010 (0.011)
Language skills	−0.030 (0.022)	−0.027 (0.025)	−0.059* (0.025)
Computer general skills	−0.013 (0.017)	0.023 (0.018)	0.012 (0.017)
N	299,011	298,877	298,877

Firm's labor demand exposure to automation technologies τ' and τ'' decile, log wage decile, broad occupational group (ISCO-1d), industry (NACE-1d), region, and minimal education level included as controls. Robust standard errors are in the parentheses. ** p<0.01, * p<0.05, + p<0.1

Table 17 Average treatment effects of skill presence on automation exposure to technology τ, estimated using the Augmented Inverse Probability Weighting estimator

	Panel A			Panel B		
	$ATE^{\text{AI and ML}}$	ATE^{Software}	ATE^{Robotics}	$ATE^{\text{AI and ML}}$	ATE^{Software}	ATE^{Robotics}
Social skills	0.018** (0.002)	0.030** (0.003)	0.011** (0.003)	0.015** (0.003)	0.022** (0.003)	0.007* (0.003)
Cognitive skills (narrow)	0.000 (0.003)	0.008* (0.003)	−0.021** (0.004)	0.003 (0.003)	0.005 (0.003)	−0.014** (0.004)
Character skills	0.008** (0.003)	0.021** (0.003)	0.017** (0.003)	0.007* (0.003)	0.016** (0.003)	0.016** (0.003)
Hand-foot-eye coordination	−0.023** (0.002)	−0.025** (0.002)	−0.021** (0.003)	−0.022** (0.002)	−0.028** (0.003)	−0.021** (0.003)
Finger dexterity skills	0.005+ (0.003)	0.010** (0.003)	0.011** (0.003)	0.008** (0.003)	0.011** (0.003)	0.014** (0.003)
Software-specific skills	−0.045** (0.006)	−0.030** (0.006)	−0.069** (0.007)	−0.058** (0.006)	−0.047** (0.006)	−0.082** (0.007)
People management skills	−0.018** (0.003)	0.000 (0.004)	−0.029** (0.004)	−0.030** (0.004)	−0.016** (0.004)	−0.038** (0.004)
Writing skills	−0.030* (0.014)	0.008 (0.015)	−0.003 (0.016)	−0.046** (0.016)	−0.012 (0.017)	−0.015 (0.018)
Customer service skills	0.030** (0.004)	0.049** (0.004)	0.040** (0.005)	0.033** (0.004)	0.048** (0.004)	0.043** (0.005)
Physical skills	−0.031** (0.016)	−0.024 (0.018)	−0.027 (0.020)	−0.033** (0.017)	−0.032+ (0.019)	−0.031 (0.022)
Financial skills	−0.054** (0.009)	−0.041** (0.010)	−0.068** (0.011)	−0.070** (0.009)	−0.067** (0.010)	−0.087** (0.011)
Machine learning/AI skills	−0.070 (0.045)	−0.089* (0.042)	−0.036 (0.055)	−0.003 (0.066)	−0.087 (0.058)	0.016 (0.072)
Project management skills	−0.023** (0.009)	0.001 (0.009)	−0.004 (0.010)	−0.028** (0.009)	−0.012 (0.010)	−0.010 (0.011)
Language skills	−0.020 (0.018)	−0.010 (0.021)	−0.040* (0.020)	−0.020 (0.021)	−0.012 (0.023)	−0.047* (0.024)
Computer general skills	0.000 (0.018)	0.031 (0.020)	0.017 (0.018)	−0.008 (0.017)	0.027 (0.017)	0.018 (0.016)
N	324,377	316,508	316,508	299,011	298,877	298,877

Panel A includes controls for firm-level labor demand exposure to automation technologies τ' and τ'' deciles, broad occupational group (ISCO-1d), industry (NACE-1d), region, and minimum education level. *Panel B* additionally includes log wage decile as a control. Robust standard errors are in parentheses. ** p<0.01, * p<0.05, + p<0.1

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Data availability

The data used in this paper, sourced from Profesia, are available for research purposes. However, there is no formal procedure or existing mechanism to obtain these online vacancy data; therefore, I recommend contacting Profesia directly at (https://www.profesia.sk), or employing web scraping techniques. The data used to obtain the textual corpus of patents are sourced from Google Patents Public Data, provided by IFI CLAIMS Patent Services and Google. Google Patents Public Data can be directly obtained from Google Cloud (https://console.cloud.google.com/marketplace/product/google_patents_public_datasets/google-patents-public-data?pli=1). Due to size limitations, the raw patent text data are not shared. However, detailed information is provided in the methodology section, enabling the replication of queries and analysis performed on this dataset for research purposes. Lastly, computed exposure scores in this paper at the level of unit groups of ISCO-08 occupations are accessible at: (https://github.com/tomasoles/AutomationExposureISCO-08). The cleaned and structured Profesia vacancy dataset cannot be shared due to access restrictions. All other cleaning and replication files necessary to reproduce the paper's findings are available upon request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT to improve readability, grammar, and clarity. After using the tool, the author reviewed and edited the content as needed and takes full responsibility for the final version of the paper.

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