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The Value of Prompting Skills

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Abstract

With the advent of generative artificial intelligence, prompting skills are becoming increasingly relevant in the workplace. Using a discrete choice experiment (DCE), this study examines employers' hiring preferences and willingness to pay (WTP) for prompting skills and whether prompting skills can complement social skills or compensate for occupation-specific skills gaps. In the DCE, decision-makers on hiring in German firms in all sectors of the economy are asked to choose between job applicants with different skills bundles. Applicant profiles vary in five attributes: prompting skills, occupation-specific skills gaps, social skills, gender and salary expectations. We find that prompting skills increase applicants' hiring probability by 4 percent and employers are willing to pay 2 percent above the average salary of a skilled worker in their firm. This WTP is modest compared to the WTP for having matching occupation-specific skills or high social skills. However, in large firms as well as firms that have adopted or are planning to adopt AI, high prompting skills increase applicant's hiring probability by 9 percent. Moreover, prompting skills have some leverage to balance out low to intermediate social skills. Yet, higher prompting skills do not compensate for occupation-specific skills gaps. Instead of such a compensatory effect, the demand for prompting skills seems to upgrade skills requirements in jobs.

JEL classification

J23, J24, M51, O33

Keywords

prompting skills, generative AI, discrete choice experiment, willingness to pay, skills complementarities

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1. Introduction

Generative artificial intelligence (GenAI) applications are increasingly integrated in work processes and augment the work and productivity of workers across all skill levels (Brynjolfsson et al., 2025; Capraro et al., 2024; Dell'Acqua et al., 2026; Noy & Zhang, 2023). With the increased application of GenAI (Eurostat, 2025b), AI literacy is becoming a crucial skillset for many jobs (Knoth et al., 2024; Long & Magerko, 2020; Ng et al., 2021). A core skill within the broader concept of AI literacy is *prompt engineering* (Knoth et al., 2024), hereafter referred to as *prompting.*

Emerging experimental evidence shows that the use of GenAI enables higher work quality and efficiency. Notably, the gains are largest among less skilled workers (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026; Noy & Zhang, 2023), suggesting that GenAI can act as a learning catalyst (Capraro et al., 2023; Handa et al., 2023; Walter, 2024). First evidence on the relevance of prompting and AI skills in specific labor market segments for graduates in economics and business administration (Carvajal et al., 2024) and new hires in graphic design, office assistance, and software engineering (Stephany et al., 2026) suggests that prompting and AI skills increase applicants' hiring prospects.

A recent OECD report shows that firms that experience skills gaps in their workforce find GenAI helpful to compensate for these gaps by enhancing worker performance (OECD, 2025). If prompting skills increase workers' effective use of GenAI, these skills might also help closing existing skills gaps. In recent years, also the demand for social skills – i.e., the ability to work with others – has increased in occupations with high AI exposure (Green, 2024). These social skills are crucially valued and yield positive returns on the labor market. Furthermore, they have been shown to be complementary to cognitive skills as well as automation (Aghion et al., 2023; Deming, 2017; Navarini, 2023; Weinberger, 2014). In this paper, we aim to answer three questions that remain unanswered in the current literature:

(1) How do employers value prompting skills?
(2) Is the value of prompting skills higher for applicants with higher social skills?
(3) Can prompting skills compensate for occupation-specific skills gaps in the hiring process?

We include a discrete choice experiment (DCE) in a panel study for a representative sample of German firms. In this DCE, decision-makers on hiring are asked to choose between two job applicants with different skills bundles. The applicant profiles vary in five attributes: (1) prompting skills, (2) a gap in occupation-specific skills, (3) social skills, (4) gender, and (5) their salary expectation relative to a skilled worker in the firm. Moreover, we examine whether employers' skills preferences are related to firm characteristics such as firm size, sector of industry, region, and firms' AI adoption.

We find that prompting skills are valued in the labor market, although the effect size is modest compared to employers' dominant preferences for occupation-specific skills matches and high social skills: Employers' average willingness to pay (WTP) for high prompting skills is two percent above the average salary of a skilled worker in the firm. In comparison, the penalty for having occupation-specific skills gaps is up to 14 percent below-average salary, whereas employers are willing to reward high social skills with up to 15 percent above-average salary. When we include interaction effects between the various skills, we do not find that the value of prompting skills is enhanced when applicants also have high social skills. Instead, our results suggest that prompting skills increase applicants' hiring prospects when their social skills are low. Furthermore, intermediate or high prompting skills do not significantly offset occupation-specific skills gaps. Heterogeneity analyses show that large firms have a much higher demand for high prompting skills than small and medium enterprises (SMEs). Moreover, firms that have adopted or are planning to adopt AI have a higher demand for high prompting skills than firms that are not yet considering AI adoption.

Our study contributes to the literature in three ways. First, we add to the literature on AI and changing skill demands (Garcia-Lazaro et al., 2025; Salomons et al., 2025; Stephany & Teutloff, 2024) by focusing on the relevance of prompting skills for skilled workers in all sectors of the economy. In that, we test the effect of applicants' prompting skills on hiring probability and evaluate the monetary value of these skills in the German labor market. Second, we add to existing hiring experiments on the value of digital or AI skills, and prompting (Carvajal et al., 2024; Stephany et al., 2026; Zamberlan et al., 2024) by quantifying the interplay between prompting, occupation-specific and social skills from a firm perspective. Third, we add to the literature on skills mismatches (Allen & van der Velden, 2001; McGuinness et al., 2018; van der Velden &

Verhaest, 2017) by examining whether employers may see prompting skills as compensatory to workers' gaps in occupation-specific skills or as an upgrading of occupational skills requirements.

2. Background and Hypotheses

2.1 The Rising Demand for Prompting Skills

GenAI offers various use-cases for commercial use at low cost and can support firms regardless of their size, sector or specialization (OECD, 2025). This is a crucial distinction from previous AI applications that were often only accessible to high-resource firms (Capraro et al., 2024). As the integration of GenAI tools in work processes does not require substantial organizational or technological investments (Dell'Acqua et al., 2026), these tools can better support businesses in lower-resource settings (Capraro et al., 2024; OECD, 2025). This high accessibility of GenAI is also reflected in European statistics on increasing AI utilization in SMEs (Eurostat, 2025a, 2025b; OECD, 2025).

Various studies show that AI has created new potential for productivity growth through the automation of nonroutine tasks that require tacit knowledge (Acemoglu & Restrepo, 2018; Autor, 2015; Brynjolfsson et al., 2025). GenAI in particular excels at automating nonroutine tasks such as writing (Noy & Zhang, 2023), programming (Peng et al., 2023), and ideation (Boussioux et al., 2023). Moreover, GenAI tools increase worker performance by complementing workers in jobs that require effective communication and social skills, such as consulting (Dell'Acqua et al., 2026) and customer service (Brynjolfsson et al., 2025).

Simultaneous to the rise of research on the effects of GenAI on work output, other studies aim to understand the determinants for the quality of this output. In this context, the concept of AI literacy is gaining scholarly attention. AI literacy comprises the skill set required to effectively work with AI and critically question its outputs (Knoth et al., 2024; Long & Magerko, 2020; Ng et al., 2021; Walter, 2024). It is seen as a crucial skill set for the future, whose implementation in educational curricula is being recommended (Capraro et al., 2024; Handa et al., 2023; Hashmi & Bal, 2024). The major skill within AI literacy in the context of GenAI is *prompting* (Knoth et al., 2024), which is defined as the construction of inputs for GenAI models to lead them towards the desired output (Bansal, 2024; Robertson et al., 2024), by creating an interactive dialogue between GenAI and humans (Oppenlaender et al., 2024). As a way of effectively communicating with GenAI systems, prompting is becoming increasingly important (Bansal, 2024; Walter, 2024). Early research on prompting suggests that well-crafted prompts relate to higher work quality and reproducibility (Grabb, 2023; Park et al., 2023) and prompting is increasingly understood as a quantifiable and acquirable skill (Bansal, 2024; Capraro et al., 2024; Handa et al., 2023; Hashmi & Bal, 2024; Knoth et al., 2024; Oppenlaender et al., 2024). Under this premise, prompting skills enable workers to produce higher quality GenAI output in a more efficient manner. This aligns with human capital theory (Becker, 1962), in that a worker with prompting skills can be understood as more productive for the firm compared to a worker without prompting skills.

Beyond being measurable human capital, prompting skills may additionally act as a signal of being a more capable employee, which aligns with signaling theory postulating that –at the time of a hiring decision– firms infer applicants' productive capacity from their observed attributes (Spence, 1973). From this perspective, recruiters may interpret AI skills as a proxy for other favorable attributes such as adaptability and future-orientation (Stephany et al., 2026). Similar studies provide evidence that AI and prompting skills serve as positive hiring signals (Carvajal et al., 2024), even reducing common hiring penalties of older and educationally disadvantaged workers (Stephany et al., 2026).

Based on above this reasoning, we formulate the following two hypotheses:[1]

H1: *Employers prefer to hire applicants with intermediate or high prompting skills compared to those with low prompting skills*.

H2: *Employers are willing to pay applicants with intermediate or high prompting skills a higher salary compared to those with low prompting skills.*

2.2 Prompting and Skills Complementarities

While the rise of AI may lower the demand for (now) automatable skills, it may increase the demand for skills in which humans complement technology, so that productivity is enhanced (Acemoglu & Restrepo, 2018; Autor et al., 2003). Such complementary skills occur in numerous frameworks for 21st century skills. In particular, social skills are increasingly highlighted alongside information-technology skills across a multitude of these frameworks (van Laar et al., 2017; Voogt & Roblin, 2010). Prior empirical research has proven the increasing value of social skills in the

[1] The wording and order of our hypotheses in this paper deviates from the initial, preregistered hypotheses. These adaptations were made solely to support the structure and readability of the paper, and do not reflect any changes in content. The original wording of hypotheses can be found in the preregistration of our study under http://doi.org/10.17605/OSF.IO/5W6D3.

labor market (Deming, 2017). Defined as the ability to work with others, social skills yield positive returns for workers and are becoming more complementary to automation and cognitive skills over time (Aghion et al., 2023; Deming, 2017; Navarini, 2025; Weinberger, 2014). The increasing demand for these complementary skills has been related to higher firm productivity, "perhaps indicating that some firms take better advantage of modern technologies" (Deming & Kahn, 2018, p. 357). Moreover, social skills are demanded in occupations with greater AI exposure (Green, 2024) and gradually embedded in educational curricula exposed to digital technologies (Salomons et al., 2025). These studies suggest that social skills may be complementary to AI skills. Brynjolfsson et al. (2025) experimentally show that GenAI assistance can improve users' social skills, suggesting a reinforcing relationship between the two. Conditional on the positive effects of prompting skills on hiring probability, we therefore hypothesize the value of prompting skills to be higher in combination with high social skills.

H3: *Employers prefer to hire applicants with intermediate or high prompting skills when they also have higher social skills.*

Another common finding across more recent studies is that productivity gains from GenAI are largest for low-skilled workers (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026; Noy & Zhang, 2023). This discerns GenAI from previous technological innovations being skill-biased in that they have complemented those with higher skills more, increasing their productivity and wages (Bresnahan et al., 2002; Lazear et al., 2022). With its novel capabilities, GenAI tools however "seem to exhibit a worker-complementary 'inverse skill-bias'" (Capraro et al., 2024, p. 6). In similar vein, a recent OECD report shows that SMEs disclose that the integration of GenAI can support the compensation of workforce shortages and skills gaps[2] (OECD, 2025). While the growing evidence of GenAI productivity effects implies that firms might be increasingly aware of the opportunity to use GenAI to offset skills deficits, Stephany et al. (2026) provide evidence that the signaling power of AI skills is more beneficial for lower educated applicants. Moreover, in a more general context of digital skills, Zamberlan et al. (2024) find that intermediate and advanced digital skills can compensate for occupational skills mismatches in hiring, especially when candidates are underqualified. Therefore, employers might view prompting skills as potentially

[2] As a subtype of skills mismatches, skills gaps are most often measured from the employer perspective and defined as a perceived lack of workers' necessary skills to perform their current job (McGuinness et al., 2018).

useful in bridging applicants' deficits in occupation-specific skills. Consequently, our fourth hypothesis reads as follows:

H4: *High prompting skills can offset a slight gap in occupation-specific skills.*

3. Data and Descriptive Statistics

3.1 Data

The design, sample and primary outcome measures of this study were preregistered prior to data collection.[3] The DCE is integrated in the 2025 wave of the *Establishment Panel on Training and Competence Development* administered by the German Federal Institute for Vocational Education and Training (BIBB Training Panel). This annual survey inquires a representative sample of around 4,000 German firms about qualification needs in the context of current labor market trends. The initial sample of firms has been drawn from the establishment database of the German Federal Employment Agency that includes all addresses of firms in Germany with at least one employee subject to social security contributions. Each annual probability sample – including refreshment firms compensating for panel attrition – is stratified across firm size, industry, and apprenticeships. The data are collected by independent interviewers via face-to-face interviews (CAPI), computer assisted web interviews (CAWI) or telephone interviews (CATI). Regardless of the interview mode, the DCE section is presented to respondents on a screen to facilitate visual representation of the choice task. Participation is voluntary and unincentivized, and respondents are decision-makers representing the firm, such as owners, managing directors, branch managers or human resources managers, among others.

3.2 The Discrete Choice Experiment

We design a DCE to reveal decision-makers' trade-offs in hiring with respect to workers' skills. DCEs encompass an assessment of hypothetical scenarios through stated preferences. Especially in DCE designs that present paired choice options and force participants to make trade-offs, stated preferences have been shown to be close to real preferences (Hainmueller et al., 2015). Building on this, our DCE requires respondents to repeatedly make a choice between two distinct job applicants presented side by side. In the introduction to the DCE, we define three applicant traits to be fixed: completed vocational education, relevant professional expertise and five years of

[3] The preregistration is available on OSF under http://doi.org/10.17605/OSF.IO/5W6D3.

working experience. We name these traits to ensure all applicant profiles are perceived comparably regarding their age and labor market experience.

The subsequently presented applicant profiles vary exogenously in five attributes, namely, prompting skills, a gap in occupation-specific skills, social skills, gender and their salary expectation relative to skilled workers in the firm. The skills attributes and salary expectation are included to quantify employers' trade-offs between the various skills and the WTP for these skills, whereas gender is merely included to control for its potential effect on hiring preferences (see Carvajal et al. (2024)). Table 1 presents an overview of the attributes, their respective levels and the wording in which they were presented to respondents.

[insert Table 1 here]

To ensure equal understanding of the skills and discern prompting from social skills, respondents are provided with corresponding definitions in the instructions preceding the DCE.[4] The definition of prompting skills is presented to respondents as follows: *"Generative AI enables the creation of fundamentally new content, such as text or images. An example of such an AI application is ChatGPT. Competence in generative AI—commonly referred to as prompting—describes the ability to formulate clear and precise instructions for the AI in order to obtain the desired outputs".* Social skills are presented as "*an applicant's teamwork skills, effective communication and cooperation, and intercultural competence*".

Combining the number of levels per attribute yields a full factorial design of 2 x 3 x 3 x 3 x 3 = 162 combinations per applicant profile, that randomly combined into choice sets with two profiles each, would create (162*161)/2 = 13,041 possible choice sets. Due to the inefficiency of a DCE design of such size, we opt for a fractional design instead. In that, we follow the principles for maximum efficiency in choice sets based on the Stata module d-create (Hole, 2016; Zwerina et al., 1996), while allowing for some overlapping attribute levels between profiles to enhance realism (e.g., same gender choice sets) and enable the calculation of attribute interactions. Moreover, we do not exclude any specific combinations of certain attribute levels. As a result, our design yields 400 unique choice sets that are randomly blocked into 50 decks of eight sets.

[4] An original (German) and translated version of the full instructions preceding the DCE as they were presented to respondents can be found in Appendix B.

3.3 Sample

The 2025 wave of the BIBB Training Panel comprises a full sample of 4,026 firms. Due to unforeseen technical reasons, the random allocation of decks to participants was merely correctly provided to a subsample of 1,709 firms that were interviewed remotely via CATI (43 percent, compared to 37 percent CAPI, and 20 percent CAWI). Out of this subsample, 1,036 firms have answered at least one choice set. In order to rule out any systematic differences between our CATI-subsample and the full BIBB Training Panel, we perform selectivity analyses. Specifically, we regress an indicator for subsample inclusion on observable characteristics such as industry, firm size and the decision-making authority, gender, tenure and educational background of the decision-maker in the firm. Results are given in Table A1. Except for the variables of decision-making authority, region and single industries, we do not find significant differences between the subsample and the full sample.

Moreover, we exclude respondents who are not involved in making hiring decisions as well as those who have not made any choice in the DCE. In total, we obtain a working sample of 992 firms, yielding 15,660 observations for our main analysis based on respondents' repeated choices in the DCE. Table 2 displays summary statistics of observable firm characteristics and items on AI adoption. SMEs are commonly defined as firms that employ less than 250 employees (Eurostat, 2021). Based on their number of employees subject to social security contributions in 2024, approximately 81 percent of the firms in our working sample can be categorized as SMEs. The represented industries pertain to the German standard classification WZ 2008.[5] With approximately 67 percent, the majority of firms are in industries which can be mapped to the tertiary (service) sector, compared to 28 percent in the secondary, and five percent in the primary sector. The vast majority of surveyed firms are located in Western Germany (83 percent).

[insert Table 2 here]

The BIBB Training Panel also contains information about the current or planned adoption of various digital technologies in the firm. Among those, three types of AI are distinguished: (1) AI in physical work processes (e.g., production and maintenance), (2) AI in non-physical work processes (e.g., marketing or big data analytics) and (3) GenAI (e.g., ChatGPT, DeepL). Current

[5] The WZ 2008 is comparable to the largest categories (called "sections)" defined by the International Standard Industrial Classification (ISIC Rev. 4).

adoption of AI is lowest for AI in physical work processes (16 percent), while it is highest for GenAI (46 percent). Firms planning to adopt these three types of AI in the near future range from 10 to 15 percent.

4. Empirical Framework

To identify decision-makers' relative preferences over observable applicant attributes, we estimate mixed logit models. Compared to conditional logit models, the mixed logit allows us to account for the sequence of choices per individual and allow for preference heterogeneity across individuals (Revelt & Train, 1998; Train, 2009). Each decision-maker n makes repeated choices between applicants k and j. The utility U that n derives from selecting the applicant j in choice set t is specified as

$$U_{njt} = \beta'_n X_{jt} + \varepsilon_{njt},$$

where β_n denotes a vector of unobservable preferences, while X_{jt} is a vector of observable applicant attributes, and ε_{njt} is an unobserved error term that is assumed to be independently and identically distributed (i.i.d.) with a type I extreme value distribution. Under the utility maximization assumption, decision-maker n selects applicant j in choice set t if and only if $U_{njt} > U_{nkt}$, $\forall\, k \neq j$.

The mixed logit model captures unobserved heterogeneity in hiring preferences by allowing the preference parameters β_n to vary across decision-makers and firms. The distribution of β_n is given by $f(\beta_n|\theta)$, where the parameter vector θ characterizes the coefficients' mean and covariance. The unconditional probability that decision maker n hires applicant j in choice set t is obtained by integrating the conditional logit probability over the distribution of β_n (Revelt & Train, 1998; Train, 2009):

$$P_{njt} = \int \left(\frac{\exp(\beta'_n X_{jt})}{\sum_k \exp(\beta'_n X_{kt})} \right) f(\beta_n|\theta) d(\beta_n).$$

Conditional on β_n, the sequence of hiring decisions made by n in all T choice sets is given by the product of standard logit choice probabilities:

$$S_n(\beta_n) = \prod_{t=1}^{T} \frac{\exp(\beta'_n X_{jt})}{\sum_k \exp(\beta'_n X_{kt})} .$$

Because β_n is unobserved, the unconditional probability for the full sequence of hiring decisions is obtained by integrating over the distribution $f(\beta_n|\, \theta)$.

$$S_n(\theta) = \int S_n(\beta_n) f(\beta_n|\theta) d(\beta_n).$$

This integral is approximated using simulated maximum likelihood. Specifically, we approximate $\hat{S}_n(\theta)$ by drawing R values of β_n from its distribution $f(\beta_n|\theta)$, computing $S_n(\beta_n)$ for each draw, and approximating the choice probability by averaging $S_n(\beta_n)$ across simulations:

$$\hat{S}_n(\theta) = \frac{1}{R} \sum_{r=1}^{R} S_n(\beta_n^{r|\theta}),$$

where R denotes the number of simulation draws and $\beta_n^{r|\theta}$ is the r^{th} draw from $f(\beta_n|\theta)$. $\hat{S}_n(\theta)$ is then the simulated probability of the choice sequence used in the simulated log-likelihood function

$$LL(\theta) = \sum_n \ln S_n(\theta),$$

which is maximized to obtain the parameter estimates. We use 300 Halton draws for simulation.

5. Results

5.1 Main Effects

Table A2 compares the effects of applicant attributes on their hiring probability across various model specifications, reported in log-odds. The signs and significance of mean coefficients are consistent across all models. To account for the sequence of choices per individual and allow for preference heterogeneity across decision-makers, we prefer the mixed logit model with uncorrelated random parameters over the conditional logit model.[6] Table 3 shows the average marginal effects[7] derived from our mixed logit specification as well as the WTP estimations.[8] The latter are given in percentages and reflect how much an employer is willing to pay in exchange for each skill attribute, relative to the average salary of a skilled worker in the firm.

[insert Table 3 here]

All attribute levels have a significant impact on applicants' hiring probability at the one percent level. Intermediate and high prompting skills significantly increase the hiring probability, by 4.3% and 5.2%, respectively. These effect sizes are rather modest compared to those of

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6 We also estimate a mixed logit model with correlated random parameters (See Table A2). This model allows preference heterogeneity to be correlated across attributes (Hensher & Greene, 2003). We find somewhat larger effect sizes for some attributes, suggesting that the results of the uncorrelated model could be interpreted as conservative.

7 For the computation of marginal effects, we use post-estimation command mixlelast by Zeigermann (2024).

8 As the salary expectation of applicants was included in the DCE as two discrete levels (3% or 6% higher than an average salary of a skilled worker in the firm), for the WTP estimation, we construct a continuous salary attribute to capture the average marginal disutility for a applicants' salary expectation of 1% above an average skilled worker in the firm.

occupation-specific skills gaps and social skills. In terms of WTP, employers are willing to pay a 2% to 2.5% above-average salary for applicants with intermediate or high levels of prompting skills compared to those with low prompting skills. These findings are in line with hypotheses H1 and H2.

As expected, the occupation-specific skills gaps and social skills are the most important drivers of applicants' hiring probability. Depending on their extent, gaps in occupation-specific skills are penalized by a negative hiring probability of 14% to 32% with a WTP penalty of approximately 6% to 14% below the average salary of a skilled worker. Social skills are highly valued and correspond to a 20% to 34% higher hiring probability with a WTP of 9% to 15%. The marginal effects for applicants' increased salary expectations are both negative and significant, where the 3% salary increase influences the hiring probability considerably less than the 6% increase.

As a robustness check, we examine whether the effects of our DCE attributes on applicants' hiring probability differ based on respondents' decision-making authority in the hiring process. In Table A3, we compare our estimates in a sample split among respondents with full versus shared decision-making authority. The signs, significance and effect sizes all remain stable.

5.2 Attribute Interactions

Table 4 shows the interaction effects between the skills attributes as hypothesized in H3 and H4. To explore potential complementarity between prompting and social skills, we include interactions between all levels of these attributes. We show a significant positive relation between intermediate prompting and intermediate social skills. Compared to the reference category of applicants with low prompting and low social skills, applicants who have both skills at the intermediate level have a 4% higher hiring probability. However, we do not find this positive interaction for higher skill levels: High social skills do not significantly interact with either level of prompting skills. Based on these results, we cannot confirm hypothesis H3, although our results suggest that – compared to applicants with low prompting and low social skills – intermediate prompting skills seem to have some leverage when applicants only have low or intermediate social skills. A robustness check shows that this finding is largely consistent across decision-makers' authority level in hiring processes (see Table A3).

[insert Table 4 here]

To investigate our hypothesis of a potential compensatory effect of prompting skills for applicants who have a gap in their occupation-specific skills, we add interactions between all levels of the respective skills attributes. We find that the interaction between intermediate prompting skills and a slight skills gap is marginally significant, indicating a 3% lower hiring probability compared to the reference group of applicants with low prompting skills and an occupation-specific skills match. This shows that intermediate prompting skills exacerbate the negative effect of a slight skills gap in applicants' occupation-specific skills. We do not find significant interaction coefficients for high prompting skills with both the slight and the considerable skills gaps. We thus lack substantial evidence to support hypothesis H4.

As shown in Table A3, among decision-makers who are fully responsible for hiring decisions, we do observe a positive, significant interaction for high prompting skills and a slight occupation-specific skills gap compared to applicants with low prompting and an occupation-specific skills match. However, in this analysis the additive effects of intermediate and high prompting skills for applicants with a full occupation-specific skills match that consistently remained significant across heterogeneity analyses, turn insignificant. For this relatively small subgroup, the effect of high prompting skills seems to be absorbed entirely by its interaction with a slight occupation-specific skills gap.

5.3 Heterogeneity Analysis

To explore differences in the demand for prompting skills based on firm characteristics, we first perform heterogeneity analyses on firms' size, sector of industry and region, as shown in Table 5. To our base equation, we add the interaction term $X_{jt} * Z_n$, yielding,

$$U_{njt} = \beta'_n X_{jt} + \gamma' X_{jt} Z_n + \varepsilon_{njt},$$

with Z_n representing a vector of observable firm characteristics, and γ a vector of coefficients for the interaction term between job attributes X_{jt} and observables Z_n.

[insert Table 5 here]

When interacting prompting skills with firm size, we find that in SMEs (i.e., firms with at most 250 employees) the demand for high prompting skills is rather similar to the effect size for the pooled sample. However, in large firms the hiring probability of applicants with high prompting skills is 9% higher than for those with low prompting skills, which is doubling the size of the initial effect. The interaction coefficient is significant at the five percent level. We repeat this procedure with an alternative definition of the firm size dummy based on a median split. Though the interaction coefficient is smaller, the findings are similar: Firms with an above-median number of employees are 7% more likely to prefer an applicant with high prompting skills. The interaction effect is significant at the five percent level. We do, however, not find significant interaction effects when interacting prompting skills with the firm sector or region.

Next, we explore whether firms that have already adopted or are planning to adopt AI have a higher demand for prompting skills than firms that are not considering AI adoption in the near future.[9] As mentioned in Section 3.3, we here distinguish between three types of AI adoption: (1) AI in physical work processes (e.g., production and maintenance), (2) AI in non-physical work processes (e.g., marketing or big data analytics) and (3) GenAI (e.g., ChatGPT, DeepL). Table 6 presents heterogeneity in the demand for prompting skills with respect to firms' current or planned AI adoption. The table shows that for all three distinguished types of AI adoption, the non-adopting firms retain a significantly positive effect of both levels of prompting skills on applicants' hiring probability, ranging between 2% and 4%. However, firms with planned or actual AI adoption in physical work processes (Column 1) or non-physical work processes (Column 2) are significantly more likely to prefer applicants with intermediate and high prompting skills than their non-adopting counterparts. Specifically, the hiring probability for applicants with high prompting skills is approximately 9% higher than for those with low prompting skills. However, among GenAI adopters, the interaction effect is only marginally significant for high prompting skills, and insignificant for intermediate prompting skills.

[insert Table 6 here]

6. Discussion and Conclusion

Consistent with recent studies on the growing importance of AI literacy, we find that employers already value prompting skills despite the relatively early diffusion stage of GenAI. In our DCE, applicants with prompting skills increase their hiring probability by 4% to 5%, and

[9] The correlation between firm size and AI adoption in our working sample ranges between $r = .18$ and $r = .25$, depending on the type of AI adoption. To account for this correlation and check whether the effects of prompting skills are driven exclusively by one of the variables, we split our sample into four subgroups: adopters and non-adopters among large firms and SMEs. We run separate mixed logit models within these groups and find that the positive effects of high prompting skills persist in each subgroup, for all three types of AI applications, with a consistent pattern of larger effect sizes for larger firms over SMEs and adopters over non-adopters.

employers are willing to pay a 2% above-average salary for applicants with prompting skills. This positive effect of prompting skills is in line with similar hiring experiments for graduates in economics and business administration (Carvajal et al., 2024) and specific occupations in the fields of graphic design, office assistance, and software engineering (Stephany et al., 2026). Furthermore, our result mirrors the positive effect of advanced digital skills in a hiring scenario in which occupational requirements and candidate qualifications are well-matched (Zamberlan et al., 2024). As previous evidence has confirmed that GenAI increases worker productivity (Brynjolfsson et al., 2025; Capraro et al., 2024), we argue that employers anticipate the enhanced human capital of a new hire who interacts with GenAI effectively.

Among our sample of decision-makers in hiring across firms in all sectors of the German economy, the distinction between intermediate and high levels of prompting skills appears to be less relevant for their positive effect. However, our heterogeneity analysis reveals some nuance in the effect sizes. While SMEs significantly prefer intermediate and high prompting skills by almost 4%, larger firms prefer high prompting skills more strongly by 9%. This finding suggests that despite the increased opportunities through GenAI for SMEs (OECD, 2025), larger firms have a more pronounced preference for new hires with high prompting skills, which may possibly reflect greater awareness of GenAI's productivity-enhancing potential among larger organizations (Czarnitzki et al., 2025). Similarly, AI adopters assess high levels of prompting to be particularly beneficial, which is in line with self-reported measures of expected productivity gains through AI (Licht & Wohlrabe, 2026). This strongly suggests that these firms intuitively grasp the implied increase in human capital and its potential for productivity growth.

However, the persistent positive effect of prompting skills on applicants' hiring prospects in SMEs and non-adopting firms shows that prompting skills are broadly valued in the labor market for skilled applicants. Even though non-adopting firms cannot directly benefit from prompting skills, they still seem to value them already. As a complement to our previous human capital explanation, this might be explained by signaling theory, in that firms may have inferred other skills or applicant traits – such as adaptability or future-orientation – through prompting skills (Stephany et al., 2026).

When comparing the effect sizes of our skills attributes, the effect of prompting skills is rather modest, while occupation-specific skills matches and high social skills considerably benefit applicants' hiring probability. Considering the specificity of prompting skills compared to the much broader categories of occupation-specific and social skills, the smaller effect sizes are not surprising. Building on experimental studies which established that AI skills increase in value based on their complementarity with other skills (Stephany & Teutloff, 2024), we further test interactions between these skills. However, we reject our hypothesis that high prompting skills enhance hiring chances more strongly in conjunction with high social skills. Instead, we find a positive interaction effect for applicants with prompting and social skills at intermediate levels. Moreover, the positive effect of prompting persists for applicants with low social skills. These results suggest an alternative notion to our hypothesis, indicating that prompting skills may have leverage to balance out low to intermediate levels of social skills.

Similarly to Zamberlan et al. (2024), we also tested whether prompting skills may be perceived to potentially compensate for skills mismatches within occupations – particularly focusing on occupation-specific skills gaps. However, in our hiring scenario for a vocationally trained worker with some professional expertise, employers – on average – were not willing to tolerate deficits in occupation-specific skills, even when applicants had high prompting skills. Prompting skills may not be perceived as a sufficiently strong predictor for improved worker performance to offset the negative effects of skills deficits. Nevertheless, prompting skills do seem to have positive value in the labor market when applicants' occupation-specific skills match the job requirements. This aligns with firms' persisting need for well-skilled workers despite GenAI potential (OECD, 2025), implying that employers' demand for prompting skills seem to upgrade skills requirements.

It should be noted that our findings are time-specific to a phase of early, yet rapidly increasing GenAI diffusion on the German labor market (Czarnitzki et al., 2025). Especially considering the rapid progress of GenAI models and rise of agentic AI systems (OECD, 2026), it would be valuable to track the development of employers' hiring preferences and their WTP for prompting skills, as well as complementarities with other relevant hiring criteria over time. Nevertheless, our study acts as a first step to assess whether firms' hiring preferences are already aligned with the fast development of GenAI across the economy.

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Data Statement

The authors do not yet have permission to share the data. A publication of the data is planned throughout the course of 2027. Once the data is published, the data and code will be added to the OSF repository containing the pre-registration: https://doi.org/10.17605/OSF.IO/5W6D3

Declaration of Generative AI

During the preparation of this work, the author(s) used Claude to support with clarity and structure of the manuscript, and DeepL for the translation of DCE instructions (Appendix B). The author(s) reviewed and edited the output as needed and take full responsibility for the content of the published article.

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Tables

Table 1: *Overview of DCE attributes and levels as presented to the respondents*

Attribute	Displayed as	Level 1	Level 2	Level 3
Prompting skills	Generative AI skills (prompting)	Low	Intermediate	High
Gap in occupation-specific skills	Occupation-specific skills compared to vacancy	Match with vacancy	Slightly less	Considerably less
Social skills	Social skills	Low	Intermediate	High
Gender	Gender	Male	Female	
Salary expectation	Salary expectation relative to the average skilled worker in your firm	Average	3% higher	6% higher

Column (1) shows the attribute titles as they are referred to in this paper, whereas column (2) displays the labels as they are presented to the respondents in the DCE. The labels differ from the reference titles to facilitate comprehensibility of the attributes for the respondents.

Table 2: *Number of respondents and corresponding percentage shares in working sample*

	N	%
Individuals in working sample	992	100
Firm size		
0–249 employees (SMEs)[10]	799	80.5
250 + employees	193	19.5
Industry (WZ 2008)		
Agriculture/Mining/Energy	54	5.4
Manufacturing	222	22.4
Construction	52	5.2
Trade & Repair	129	13.0
Business-related services	163	16.4
Other, mainly personal services	137	13.8
Medical services	119	12.0
Public service and education	116	11.7
Region		
West Germany	818	82.5
East Germany	174	17.5
AI in physical work processes (e.g., production, maintenance)		
Adopted	155	15.6
Adoption planned	148	14.9
Neither adopted, nor planned	674	67.9
Don’t know/non-response	15	1.5
AI in non-physical work processes (e.g., marketing, big data analytics)		
Adopted	256	25.8
Adoption planned	140	14.1
Neither adopted, nor planned	579	58.4
Don’t know/non-response	17	1.7
Generative AI (e.g., ChatGPT, DeepL)		
Adopted	448	45.2
Adoption planned	96	9.7
Neither adopted, nor planned	435	43.9
Don’t know/non-response	13	1.3

[10] As described in Section 3.1, the full sample of firms is drawn from a German establishment registry containing firms with at least one employee subject to social security contributions. Yet, firms with 0 employees with social security contributions at the time of data collection are retained in the panel structure of the BIBB Training Panel and reflect small businesses consisting of the firm owner and a potentially varying number of apprentices. In our analysis sample, this applies to three firms. Excluding these firms from our sample does not yield systematic differences in our estimation results. We thus retain the firms in our analysis sample.

Table 3: *Marginal effects and WTP estimates given as percentage relative to the average salary of a skilled worker in the respondent's firm*

	(1) Mixed Logit Marginal Effects	(2) WTP
Prompting skills (Ref. = Low)		
Intermediate	0.043***	2.013***
	(0.007)	(0.294)
High	0.052***	2.455***
	(0.007)	(0.308)
Social skills (Ref. = Low)		
Intermediate	0.199***	8.983***
	(0.006)	(0.465)
High	0.338***	14.637***
	(0.007)	(0.704)
Occupation-specific skills (Ref.= Skills match)		
Slight skills gap	-0.144***	-6.266***
	(0.006)	(0.375)
Considerable skills gap	-0.315***	-13.648***
	(0.007)	(0.687)
Gender (Ref. = Male)		
Female	0.021***	0.926***
	(0.005)	(0.228)
Salary expectation *(Ref. = Average skilled worker in firm)*		
3% above average	-0.048***	
	(0.006)	
6% above average	-0.138***	
	(0.008)	
Continuous salary		-1.377***
		(0.078)
Placement *(Ref. = Left)*	0.007**	0.349**
	(0.004)	(0.176)
Observations	15,660	
Individuals	992	

Column (1) shows average marginal effects from the preferred mixed logit model, with standard errors clustered at the individual level. Standard errors are given in parentheses and bootstrapped using the Krinsky-Robb method with 500 repetitions. Column (2) shows WTP in percentages relative to the average salary of a skilled worker within the surveyed firm. For the WTP estimation, a continuous salary attribute was constructed to capture the average marginal disutility for a applicants' salary expectation of 1% above an average skilled worker in the firm. ***p<0.01, **p<0.05, *p<0.1.

Table 4: *Marginal effects of prompting skills interacted with social skills and skills gaps*

	Mixed Logit Marginal Effects
Prompting skills (Ref. = Low)	
Intermediate	0.041***
	(0.013)
High	0.039***
	(0.014)
Social skills (Ref. = Low)	
Intermediate	0.178***
	(0.011)
High	0.337***
	(0.012)
Occupation-specific skills (Ref. = Skills match)	
Slight skills gap	-0.136***
	(0.010)
Considerable skills gap	-0.314***
	(0.011)
Gender (Ref. = Male)	
Female	0.021***
	(0.005)
Salary expectation (Ref. = Average skilled worker in firm)	
3% above average	-0.048***
	(0.006)
6% above average	-0.139***
	(0.007)
*Prompting skills*Social skills (Ref. = Low prompting*low social)*	
Intermediate prompting*Intermediate social	0.041**
	(0.016)
Intermediate prompting*High social	0.003
	(0.016)
High prompting*Intermediate social	0.023
	(0.017)
High prompting*High social	-0.002
	(0.016)
*Prompting skills*Occupation-specific skills (Ref. = Low prompting*skills match)*	
Intermediate prompting*Slight skills gap	-0.034*
	(0.015)
Intermediate prompting*Considerable skills gap	-0.007
	(0.017)
High prompting*Slight skills gap	0.010
	(0.016)
High prompting*Considerable skills gap	0.003
	(0.016)
Placement *(Ref. = Left)*	0.009**
	(0.004)
Observations	15,660
Individuals	992

Average marginal effects from mixed logit model. Standard errors are given in parentheses and bootstrapped using the Krinsky-Robb method with 500 repetitions, based on mixed logit model estimated with standard errors clustered at the individual level. ***p<0.01, **p<0.05, *p<0.1.

Table 5: *Marginal effects of prompting skills interacted with selected firm characteristics*

	(1)	(2)	(3)	(4)
Prompting skills (Ref. = Low)				
Intermediate	0.042***	0.033***	0.020	0.048***
	(0.007)	(0.009)	(0.029)	(0.015)
High	0.044***	0.038***	0.071**	0.057***
	(0.007)	(0.009)	(0.028)	(0.016)
Interactions between prompting skills and firm characteristics				
Intermediate*Firm size > 250 employees	0.009			
	(0.017)			
High*Firm size > 250 employees	0.042**			
	(0.017)			
Intermediate*Firm size > sample median		0.019		
		(0.013)		
High*Firm size > sample median		0.027**		
		(0.014)		
Intermediate*secondary sector			0.024	
			(0.031)	
High*secondary sector			0.020	
			(0.029)	
Intermediate*tertiary sector			-0.013	
			(0.030)	
High*tertiary sector			-0.030	
			(0.029)	
Intermediate*West Germany				-0.007
				(0.017)
High*West Germany				-0.008
				(0.018)
Placement *(Ref. = Left)*	0.007*	0.008*	0.008*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	15,660	15,660	15,660	15,660
Individuals	992	992	992	992

Coefficients of remaining applicant attributes are omitted in table. Columns (1) to (4) show average marginal effects from the mixed logit model extended with an interaction term between the levels of prompting skills and observable firm characteristics, namely firm size dummies (Column (1) above 250 employees, Column (2) above sample median of 48 employees), sector and region. Standard errors are given in parentheses and bootstrapped using the Krinsky-Robb method with 500 repetitions, based on a mixed logit model estimated with standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: *Marginal effects of prompting skills interacted with AI adoption indicator*

	(1)	(2)	(3)
Prompting skills (Ref. = Low)			
Intermediate	0.031***	0.027***	0.037***
	(0.008)	(0.008)	(0.010)
High	0.031***	0.023**	0.035***
	(0.008)	(0.009)	(0.010)
Interactions prompting skills and AI adoption			
Intermediate*AI in physical work processes	0.038***		
	(0.015)		
High*AI in physical work processes	0.062***		
	(0.015)		
Intermediate*AI in non-physical work processes		0.037***	
		(0.013)	
High*AI in non-physical work processes		0.069***	
		(0.014)	
Intermediate*GenAI			0.011
			(0.013)
High*GenAI			0.026**
			(0.013)
Placement *(Ref. = Left)*	0.008*	0.008*	0.008*
	(0.004)	(0.004)	(0.004)
Observations	15,430	15,394	15,456
Individuals	977	975	979

Coefficients of remaining applicant attributes are omitted in this table. Columns (1) to (3) show average marginal effects derived from the mixed logit model extended with an interaction term between the levels of prompting skills and an AI adoption dummy that takes the value of 1 if the firm has already adopted or is planning to adopt AI, and remains 0 if an adoption is not planned in the near future. We distinguish between three separate types of AI adoption depending on their area of application: AI in physical work processes (Column (1)), AI in non-physical work processes (Column (2)) and GenAI (Column (3)). Standard errors are given in parentheses and bootstrapped using the Krinsky-Robb method with 500 repetitions, based on a mixed logit model estimated with standard errors clustered at the individual level. The number of observations differs from the main analysis due to missing values based on non-response on AI adoption items, resulting in missing values in the interaction variables included in the mixed logit model. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendices

Appendix A: Additional Tables

Table A1: Selectivity analysis of subsample on observable firm characteristics

	(1)	(2)
Firm size *(Ref. = 0 employees)*		
1 to 19 employees	0.128	-0.001
	(0.303)	(0.519)
20 to 99 employees	-0.023	0.112
	(0.304)	(0.520)
100 to 199 employees	0.066	0.269
	(0.307)	(0.524)
200 or more employees	0.134	0.214
	(0.306)	(0.522)
Highest obtained education of decision-maker *(Ref. = No vocational qualification)*		
Completed vocational training program at a firm or school	-0.055	-0.055
	(0.244)	(0.353)
Master craftsman's certificate, technician's certificate, or comparable advanced training	-0.170	-0.155
	(0.244)	(0.353)
Degree from a university of applied sciences or a traditional university or vocational academy	-0.057	0.074
	(0.242)	(0.349)
Decision-making authority *(Ref. = Decision-maker makes hiring decisions on their own)*		
Joint hiring decisions with others	-0.015	0.017
	(0.053)	(0.083)
Supporting or advising the decision-makers in charge of hiring	-0.171**	0.129
	(0.070)	(0.110)
Not involved in hiring decision	-0.067	-0.204
	(0.103)	(0.158)
Tenure of decision-maker in years	0.002	0.003
	(0.002)	(0.003)
Female	0.044	-0.096
	(0.043)	(0.067)
East Germany	-0.188***	-0.081
	(0.049)	(0.080)
Industry *(Ref. = Agriculture, Mining and Energy)*		
Manufacturing	-0.004	0.075
	(0.090)	(0.138)
Construction	-0.040	0.121
	(0.114)	(0.177)
Trade and Repair	-0.033	0.264*
	(0.100)	(0.150)
Business-related services	-0.118	0.308**
	(0.094)	(0.146)
Other, mainly personal services	-0.100	0.227
	(0.094)	(0.145)
Medical services	0.100	0.221
	(0.101)	(0.151)
Public service and education	-0.147	0.334**
	(0.099)	(0.157)
Constant	-3.500	-5.217
	(3.676)	(5.630)
Observations	3,932	1,673

Selectivity analysis to test whether inclusion in the analysis sample is predicted by observable firm characteristics. Column (1) shows results from a probit regression of an indicator variable for firms interviewed in CATI mode on firm observables. Column (2) shows results from a probit regression of an indicator variable for firms within CATI mode agreeing to conducting the DCE online (*N* =) on the same observables. Column (2) includes respondents who have been presented with the correctly randomized choice sets. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Effects of applicant attributes on their hiring probability across logit models

	(1) Conditional Logit	(2) Mixed Logit Uncorrelated		(3) Mixed Logit Correlated	
		Mean	SD	Mean	SD
Prompting skills (Ref. = Low)					
Intermediate	0.195***	0.410***	0.0232	0.412***	0.437**
	(0.047)	(0.0646)	(0.185)	(0.0835)	(0.144)
High	0.371***	0.496***	-0.200	0.644***	0.599**
	(0.050)	(0.0647)	(0.308)	(0.0888)	(0.181)
Social skills (Ref. = Low)					
Intermediate	1.288***	1.932***	-0.312	2.787***	1.568***
	(0.054)	(0.0828)	(0.239)	(0.160)	(0.171)
High	2.092***	3.213***	1.346***	4.484***	2.686***
	(0.059)	(0.127)	(0.109)	(0.238)	(0.192)
Occupation-specific skills (Ref.= Skills match)					
Slight skills gap	-0.917***	-1.388***	-0.0224	-1.959***	1.059***
	(0.048)	(0.0720)	(0.142)	(0.122)	(0.133)
Considerable skills gap	-1.997***	-3.010***	1.164***	-4.102***	2.190***
	(0.055)	(0.119)	(0.113)	(0.212)	(0.176)
Gender (Ref. = Male)					
Female	0.119***	0.201***	0.491***	0.234***	0.862***
	(0.038)	(0.0512)	(0.119)	(0.0716)	(0.116)
Salary expectation (Ref. = Average skilled worker in firm)					
3% above average	-0.282***	-0.462***	0.0310	-0.618***	0.773***
	(0.0483)	(0.0620)	(0.309)	(0.0958)	(0.164)
6% above average	-0.855***	-1.314***	0.946***	-1.785***	1.578***
	(0.0505)	(0.0803)	(0.103)	(0.131)	(0.164)
Placement *(Ref. = Left)*	0.0267	0.0707*		0.0651	
	(0.0469)	(0.0392)		(0.0481)	
Observations	15,660	15,660		15,660	
Individuals	992	992		992	
Log-Likelihood	-7146.862	-3254.633		-3137.887	
AIC	14313.725	6547.266		6385.773	
BIC	14390.314	6692.784		6807.001	

Coefficients from logit models, displayed in log-odds. Standard errors clustered at the individual level in parentheses. Column (1) shows estimation results from a conditional logit model. Column (2) displays the mean coefficients and standard deviations of a mixed logit model with uncorrelated random parameters. Column (3) shows means and standard deviations for a mixed logit model with correlated random parameters. ***p<0.01, **p<0.05, *p<0.1.

Table A3: Sample split comparing full decision-making authority to shared decision-making authority

	(1) Mixed Logit		(2) Mixed Logit		(3) Mixed Logit		(4) Mixed Logit	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Prompting skills (Ref. = Low)								
Intermediate	0.387***	-0.216	0.422***	0.0289	0.127	-0.294	0.506***	0.0315
	(0.139)	(0.357)	(0.0754)	(0.226)	(0.294)	(0.354)	(0.155)	(0.230)
High	0.511***	0.796***	0.506***	-0.0129	0.138	0.732***	0.436***	-0.00718
	(0.149)	(0.244)	(0.0751)	(0.275)	(0.298)	(0.267)	(0.156)	(0.276)
Social skills (Ref. = Low)								
Intermediate	1.921***	-0.411	2.003***	0.409**	1.723***	-0.337	1.798***	0.391*
	(0.196)	(0.384)	(0.101)	(0.194)	(0.274)	(0.407)	(0.143)	(0.203)
High	3.326***	1.535***	3.291***	1.380***	3.341***	1.531***	3.280***	1.395***
	(0.325)	(0.278)	(0.153)	(0.131)	(0.383)	(0.278)	(0.183)	(0.131)
Occupation-specific skills (Ref. = Skills match)								
Slight skills gap	-1.305***	0.478	-1.456***	-0.0309	-1.513***	0.496	-1.285***	-0.0283
	(0.165)	(0.350)	(0.0850)	(0.148)	(0.264)	(0.368)	(0.128)	(0.152)
Considerable skills gap	-2.779***	1.288***	-3.189***	1.152***	-2.946***	1.298***	-3.143***	1.149***
	(0.273)	(0.248)	(0.146)	(0.132)	(0.354)	(0.249)	(0.178)	(0.133)
Gender (Ref. = Male)								
Female	0.192*	0.617**	0.213***	-0.481***	0.198*	0.667***	0.217***	-0.491***
	(0.114)	(0.267)	(0.0594)	(0.142)	(0.116)	(0.253)	(0.0598)	(0.142)
Salary expectation (Ref. = Average skilled worker in firm)								
3% above average	-0.442***	0.538**	-0.487***	0.175	-0.451***	0.545**	-0.497***	0.177
	(0.143)	(0.250)	(0.0731)	(0.222)	(0.144)	(0.248)	(0.0739)	(0.228)
6% above average	-1.462***	0.989***	-1.303***	0.925***	-1.538***	0.986***	-1.312***	0.924***
	(0.189)	(0.226)	(0.0944)	(0.125)	(0.198)	(0.229)	(0.0950)	(0.126)

Table A3 *Continued*

	(1)	(2)	(3)	(4)
*Prompting skills*Social skills*				
*(Ref. = Low prompting*Low social)*				
Intermediate prompting* Intermediate social			0.558	0.348*
			(0.348)	(0.182)
Intermediate prompting*High social			0.271	-0.0410
			(0.344)	(0.183)
High prompting*Intermediate social			0.133	0.285
			(0.345)	(0.182)
High prompting*High social			-0.122	0.0924
			(0.353)	(0.185)
*Prompting skills*Occupation-specific skills*				
*(Ref. = Low prompting*Skills match)*				
Intermediate prompting*Slight skills gap			-0.221	-0.390**
			(0.342)	(0.177)
Intermediate prompting*Considerable skills gap			0.187	-0.146
			(0.356)	(0.191)
High prompting*Slight skills gap			0.836**	-0.139
			(0.343)	(0.179)
High prompting*Considerable skills gap			0.258	-0.0374
			(0.339)	(0.183)
Placement *(Ref. = Left)*	0.0225	0.0960**	0.0403	0.113**
	(0.0859)	(0.0455)	(0.0875)	(0.0463)
Observations	3,666	11,994	3,666	11,994
Individuals	234	758	234	758

Mixed logit estimates for main results (columns (1) and (2)) and attribute interactions (column (3) and (4)) in split samples between respondents who make hiring decision on their own (columns (1) and (3), $N = 234$) and those who make them jointly (columns (2) and (4), $N = 758$). Estimates are given in log-odds. Standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Presentation of DCE to Participants

Original version:

Nachfolgend geht es noch einmal um die Fachkräfterekrutierung in Ihrem Betrieb. Bitte stellen Sie sich vor, Sie möchten für eine Stelle in Ihrem Betrieb eine neue Fachkraft einstellen. Die Stelle setzt folgende Merkmale von Bewerbern voraus:

- Eine abgeschlossene Berufsausbildung
- Ausgeprägte Fachkenntnisse im relevanten Bereich
- Mindestens 5 Jahre Berufserfahrung

Im Folgenden werden Ihnen 8-mal jeweils zwei Bewerberprofile vorgestellt, die sich in einigen Merkmalen unterscheiden. Wir bitten Sie, jedes Mal das Profil auszuwählen, das Sie am ehesten einstellen würden.

<u>Die Profile unterscheiden sich in fünf Merkmalen:</u>

- dem Geschlecht,
- der Übereinstimmung von Fachkenntnissen mit den Stellenanforderungen,
- der Kompetenz in generativer KI, das sogenannte Prompting,
- der sozialen Kompetenz sowie
- der Gehaltsvorstellung.

<u>Ansonsten sind alle anderen Merkmale identisch.</u>

Mittels generativer KI können grundlegend neue Inhalte, wie zum Beispiel Texte oder Bilder, erstellt werden. Ein Beispiel für eine derartige KI-Anwendung ist ChatGPT. Die Kompetenz in generativer KI, das sogenannte Prompting, ist die Fähigkeit, klare und genaue Anweisungen für die KI zu formulieren, sodass die KI die gewünschten Ergebnisse liefert.

Soziale Kompetenz meint hier die Teamfähigkeit, effiziente Kommunikation und Kooperation sowie interkulturelle Kompetenz eines Bewerbers.

English translation:

The following section once again focuses on recruiting skilled workers for your company. Please imagine that you want to hire a new skilled worker for a position at your company. The position requires applicants to meet the following criteria:

- Completed vocational training
- Extensive specialized knowledge in the relevant field
- At least 5 years of professional experience

Below, you will be presented with 8 sets of two candidate profiles each, which differ in several characteristics. We ask that you select the profile you would be most likely to hire in each case.

The profiles differ in five characteristics:

- gender,
- the match between occupation-specific skills with the job requirements,
- generative AI skills, known as “prompting”,
- social skills, and
- salary expectations.

All other characteristics are identical.

Generative AI can be used to create fundamentally new content, such as text or images. One example of such an AI application is ChatGPT. Generative AI skills—known as “prompting”—is the ability to formulate clear and precise instructions for the AI so that it delivers the desired results.

Social skills, in this context, refer to a candidate’s ability to work in a team, communicate and cooperate effectively, and demonstrate intercultural competence.