

Kosse, Fabian; Leffler, Tim; Woemmel, Arna

**Working Paper**

## Digital Skills: Social Disparities and the Impact of Early Mentoring

CESifo Working Paper, No. 11570

**Provided in Cooperation with:**

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

*Suggested Citation:* Kosse, Fabian; Leffler, Tim; Woemmel, Arna (2024) : Digital Skills: Social Disparities and the Impact of Early Mentoring, CESifo Working Paper, No. 11570, CESifo GmbH, Munich

This Version is available at:

<https://hdl.handle.net/10419/312080>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

## Digital Skills: Social Disparities and the Impact of Early Mentoring

*Fabian Kosse, Tim Leffler, Arna Woemmel*

## **Impressum:**

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email [office@cesifo.de](mailto:office@cesifo.de)

Editor: Clemens Fuest

<https://www.cesifo.org/en/wp>

An electronic version of the paper may be downloaded

- from the SSRN website: [www.SSRN.com](http://www.SSRN.com)
- from the RePEc website: [www.RePEc.org](http://www.RePEc.org)
- from the CESifo website: <https://www.cesifo.org/en/wp>

# Digital Skills: Social Disparities and the Impact of Early Mentoring

## Abstract

We investigate social disparities in digital skills, focusing on both actual proficiency levels and confidence in these skills. Drawing on a representative sample from Germany, we first demonstrate that both dimensions strongly predict labor market success. We then use this sample to identify gender and socioeconomic disparities in levels and confidence. Finally, using a long-run RCT panel framework with young adults, we confirm these disparities and provide causal evidence on the effects of enhancing the social environment in childhood. Assigning elementary school-aged children to a mentoring program persistently reduces socioeconomic gaps in confidence related to digital skills, but it does not affect the level of digital skills.

JEL-Codes: C930, D630, I240, J240, O330.

Keywords: digital skills, technological transformation, inequality, early childhood mentoring.

*Fabian Kosse*  
*University of Würzburg / Germany*  
*fabian.kosse@gmail.com*

*Tim Leffler*  
*University of Würzburg / Germany*  
*tim.leffler@uni-wuerzburg.de*

*Arna Woemmel*  
*University of Hamburg / Germany*  
*arna.woemmel@uni-hamburg.de*

December 2024

We are grateful to Armin Falk for providing access to the Bonn Family Panel and for his invaluable support in enabling this project. We also thank the DIW Berlin, particularly Martin Gerike, for their generous assistance with the implementation of data collection within the SOEPIS. We thank participants at the 3rd Workshop on Field Experiments in Economics and Business at TU Munich, as well as seminar attendees at the University of Glasgow, University of Hamburg, University of Mainz, LMU Munich, and the University of Würzburg for their valuable comments and suggestions. Financial support through Eleven – Verein für Kinder- und Jugendförderung e.V., the Jacobs Foundation, and the CRC TR 190 (project number 280092119) of the German Research Foundation (DFG) is gratefully acknowledged. This project was approved by the Institutional Review Board at LMU Munich (2022-12-19) and pre-registered at the AEA RCT Registry ([AEARCTR-0010874](https://doi.org/10.17605/OSF.IO/TQXC9)) and the Open Science Framework ([OSF: DOI 10.17605/OSF.IO/TQXC9](https://doi.org/10.17605/OSF.IO/TQXC9)) Please note that measures on chances and risks of digitization are part of the pre-analysis plan of the overall project, however, they address a different scope and are therefore not part of this paper.

# 1 Introduction

The rapid adoption of new digital technologies across sectors and occupations is fundamentally transforming the skills demanded in the labor market (Acemoglu, 2002, Autor et al., 2003, Babina et al., 2024, Eloundou et al., 2024, Gathmann et al., 2024). Unlike past technological shifts that focused on automating tasks and reducing the need for human labor, today’s digital transformation requires workers to engage directly with technology—demanding skills to use, navigate, and understand these tools (Alekseeva et al., 2021, Acemoglu et al., 2022, Bick et al., 2024, Bonney et al., 2024, Eisefeldt and Schubert, 2024). These digital skills are increasingly central to economic and social life, shaping individual opportunities as well as broader societal outcomes. At the macro level, innovation and growth prospects of countries depend largely on their population’s skills to master new technologies (e.g., Romer, 1990, Nelson and Phelps, 1966). At the individual level, digital proficiency enhances earnings and job prospects (e.g., Falck et al., 2021, Alekseeva et al., 2021, Humlum and Meyer, 2022). As technology continues to advance and spread across occupations and industries, the returns to digital skills are expected to grow further (Bick et al., 2024).

The growing importance of digital skills for individual and societal well-being raises critical questions: Which dimensions of digital skills are most relevant? Where do differences in digital skills originate, and do they exacerbate or mitigate existing inequalities? This study seeks to address these questions based on a comprehensive approach by adopting a two-dimensional perspective on digital skills, focusing on both absolute skill levels and confidence in those skills. Confidence in one’s skills is a critical complement to actual proficiency, particularly for emerging skills, as it shapes individuals’ willingness to invest in further learning (Horn and Loewenstein, 2021), enhances their motivation (Bénabou and Tirole, 2002), and affects their ability to persuade others of their capabilities (Schwardmann and Van der Weele, 2019).

We investigate these questions using two complementary approaches. First, we use a large representative sample from the Innovation Sample of the German Socio-Economic Panel (SOEP-IS) to descriptively analyze the determinants and consequences of digital skills. Second, we leverage a long-run randomized controlled trial (RCT) panel framework to explore the causal effects of enriching the childhood social environment, through a mentoring program, on the development of digital skills among young adults. In both samples, we elicited the same tailor-made measures: Level of digital skills is measured using cross-validated survey items (Helsper et al., 2020). Confidence in these skills is measured through a relative self-assessment that

asks individuals rate their skills relative to the general (German) population (see e.g., Schwardmann and Van der Weele, 2019).

We report three main results. First, we find that both, the level of digital skills and confidence in digital skills are similarly important for predicting income. Second, we document significant gender and parental socioeconomic status (SES) gaps in both actual proficiency and confidence in digital skills. Males show significantly higher levels of digital skills and higher confidence in their skills than females, even when controlling for actual proficiency. Parental SES gaps only exist for males, and only in the confidence dimension. Third, evidence from the long-run RCT suggests that early childhood mentoring programs, focusing on “informal learning”, can narrow this SES gap. Adult males from low SES backgrounds who participated in the mentoring program during childhood show significantly higher confidence in their digital skills today compared to their non-participating peers from similar backgrounds. We show that these findings are not driven by selective attrition. Our further analyses suggest that the treatment mainly increased the confidence in digital skills of participants with low confidence levels, rather than leading to an increase in overconfidence. Exploring the driving forces behind this long-term treatment effect indicates that only a minor share of the effect on confidence in digital skills can be explained by effects on general self-concept and self-esteem. This suggests that the treatment specifically increased confidence in the dynamic and fast developing domain of digital skills.

Overall, our findings suggest that the increasing demand for digital skills in the workplace may exacerbate existing labor market inequalities. In particular, men from higher socioeconomic backgrounds appear to be better positioned to benefit from technological change, both through their skill levels and their confidence in using new technologies. However, early childhood interventions that enrich the social environment have the potential to build confidence and potentially reduce these socioeconomic inequalities.

This paper contributes to several strands of literature. Our first contribution pertains to the consequences of digital skills for labor market success. While prior research has documented the role of actual digital proficiency in determining economic outcomes (e.g., Falck et al., 2021, Alekseeva et al., 2021), our study goes further by considering not only the level of digital skills but also confidence in these skills. With the rapid evolution of technology and the fact that digital skills are often acquired outside traditional education, it is challenging for individuals to assess their own skills relative to others. Yet many important choices and outcomes are shaped not only by actual skills but also by how individuals perceive their skills relative

to others (Dolan et al., 2021, He and Kircher, 2023). Confidence in one’s skills can significantly influence labor market success, for example, by influencing whether individuals apply for certain jobs, how they negotiate, and their motivation to pursue further skill development (Schwardmann and Van der Weele, 2019, Coffman et al., 2024). Our findings complement this literature by providing first evidence on the relationship between confidence in own digital skills and socioeconomic background. Thereby, we also contribute to the literature regarding the complementary effects of (rather) cognitive and (rather) non-cognitive skills (Heckman et al., 2006).

Our second contribution concerns the determinants of digital skills. On the one hand, while much of the prior literature on digital skill disparities has focused on access to digital tools (Goldfarb and Prince, 2008, James, 2007), our work directly emphasizes digital proficiency and confidence in digital skills in a representative sample. It extends and is in line with recent findings on the digital divide regarding gender and socioeconomic background (Saka et al., 2021, Werner and Woessmann, 2023, Carvajal et al., 2024, McElheran et al., 2024). For example, recently Humlum and Vestergaard (2024) show in a large Danish sample that male workers and those with higher incomes are about 20 percentage points more likely to use ChatGPT. Bick et al. (2024) report similar findings for the US, where adoption of generative AI is higher among more educated, younger, and male workers, though the gender gap is smaller (around 9 percentage points). On the other hand, we also contribute to the scarce literature on causal effects on digital skills. To date and to the best of our knowledge Aramburu et al. (2021) and Moore and Hancock (2022) are the only studies that explore determinants of digital skills based on RCTs. Both focus on very specific trainings and short-run outcomes. We provide causal evidence on the role of enriching the social environment on the development of digital skills using a long-term RCT. By leveraging data from the Bonn Family Panel (Falk and Kosse, 2020), we demonstrate that early-life interventions, such as mentoring programs, can significantly enhance confidence in digital skills for males from low SES backgrounds. This causal evidence also contributes to the literature on skill formation by highlighting how childhood interventions can mitigate skill and labor market inequalities (Heckman and Mosso, 2014, Cappelen et al., 2020, Kosse et al., 2020, Schunk et al., 2022, Resnjanskij et al., 2024, Berger et al., 2025, Falk et al., 2025, Sorrenti et al., 2025).

The remainder of the paper is organized as follows. The next section describes the data and methods including the survey module and the RCT. Section 3 presents results. Section 4 discusses the findings and concludes.

## 2 Measures and samples

This section describes the measures, the samples, and the randomized controlled trial used in this study. We begin by describing our measures of the level of digital skills and confidence in digital skills. We then provide overviews of the two samples that we use: the Innovation Sample of the German Socio-Economic Panel (SOEP-IS) and the Bonn Family Panel (bfp). Finally, we describe the childhood mentoring program which was implemented in form of an RCT within the bfp.

### 2.1 Measuring the level of digital skills

We measure the level of digital skills using the recently developed “youth Digital Skill Indicator” (yDSI) (Helsper et al., 2020). The yDSI is the only available digital skills measurement tool that has undergone comprehensive validation procedures, including expert consultations (face validity), cognitive interviews (content validity), pilot surveys (construct validity), and performance tests (criterion validity). For instance, participants of the validation study had to complete a series of tasks reflecting real-life digital challenges using digital devices under controlled conditions. These tasks tested the actual knowledge regarding the domains covered by the items surveyed in the questionnaire. The results indicate significant positive correlations between yDSI scores and performance test results. The scale was specifically developed for large-scale population research and includes only those items with the highest construct validity.<sup>1</sup> From the yDSI, we selected three dimensions particularly relevant to the labor market (Colombo et al., 2019, Alekseeva et al., 2021, Humlum and Meyer, 2022):

- Technical and Operational Skills (e.g., “I know how to adjust privacy settings.”).
- Programming Skills (“I know how to use programming languages such as XML, Python, Java, C++.”).
- Information Navigation and Processing Skills (e.g., “I know how to choose the best keywords for online searches.”).

The three dimensions of interest consist of 13 survey items in total and are measured on 5-point Likert scales. The exact wording can be found translated and as the original items in Table A1 and Table A2 in the appendix.

---

<sup>1</sup>We use the German version which was revised with cognitive interviews and provided to us by the research team around Natalia Waechter (Department of Pedagogy, Ludwig-Maximilians-University Munich).



## 2.2 Measuring confidence in digital skills

In line with Schwardmann and Van der Weele (2019), confidence in digital skills is measured using a relative self-assessment approach. This method asks individuals to evaluate their own skills in comparison to those of a well-defined reference group, providing a subjective measure of perceived relative competence. In this study, we assess individuals' relative confidence in their digital skills compared to the general German population. Taking the general German population as benchmark, in contrast to, e.g., peer groups, allows to abstract from social selection effects. Specifically, participants were asked the following question: "What percentage of the general population in Germany currently has poorer digital skills (in the dimensions described above) than you?".<sup>2</sup> The question aims to capture not only participants' self-perception of their digital competence but also their ability to contextualize their skills within the societal framework of digital capabilities.

Confidence in one's skills has been shown to be a critical complement to actual proficiency, particularly for emerging skills, as it shapes individuals' willingness to invest in further learning (Horn and Loewenstein, 2021), enhances their motivation (Bénabou and Tirole, 2002), and affects their ability to persuade others of their capabilities (Schwardmann and Van der Weele, 2019).

## 2.3 The Innovation Sample of the German Socio-Economic Panel

We implement our measures on digital skills in form of a new survey module in the Innovation Sample of the German Socio-Economic Panel (SOEP-IS, Richter and Schupp, 2012). The German Socio-Economic Panel is Germany's largest and most comprehensive longitudinal household survey. The SOEP-IS allows for the inclusion of custom modules which can be linked to a wide range of standard items available in the sample. Our module was conducted in the 2023 wave of the SOEP-IS, fielded from April through July 2023.

An important feature of the SOEP-IS is that it provides parental background information for adult individuals. This allows us to proxy the parental socioeconomic status (SES) of the adult individuals in the sample. This is essential for our analyses. First, we want to conduct the analyses of the SOEP-IS and the bfp as similar as possible and given the age structure in the bfp we have to use parental SES instead of

---

<sup>2</sup>The original question in German was: "Wenn wir über 'digitale Fähigkeiten' reden, meinen wir die Dimensionen, zu denen Sie sich gerade selbst bewertet haben. Was schätzen Sie: Wie hoch ist zurzeit der Anteil der allgemeinen Bevölkerung in Deutschland, der schlechter ausgeprägte digitale Fähigkeiten besitzt als Sie?"

self-acquired SES. Second, parental SES is a pre-determined variable and therefore allows for a more straightforward analysis.

To proxy parental SES in the SOEP-IS we rely on the Treiman job prestige score. The Treiman job prestige score is based on the occupation of an individual and is a measure of the societal status associated with various occupations, reflecting factors like required education and perceived societal value. Higher scores indicate more prestigious jobs, often requiring advanced education and resulting in higher income (Treiman (2013)). For our analyses we focus on the highest available prestige score among the parents. To allow for a similar analysis as for the bfp (see below), we generate a high vs low SES indicator by conducting a simple median split based on the Treiman job prestige score.

Our SOEP-IS sample consists of 1,504 individuals, 1,318 of them provided information on both of our digital skill measures. 50.8% of this sample are female. The age distribution covers the range from 18 to 95. 938 of the individuals in the sample are active on the labor market with a median gross hourly wage of 21.5 euros. For our analysis, we focus on those who are active on the labor market.

## 2.4 The Bonn Family Panel

To investigate the causal impact of enriching the social environment on the level of and confidence in digital skills, we also implemented our measures on digital skills in the Bonn Family Panel (bfp, Falk and Kosse, 2020).

The bfp was originally assembled in 2011. For the panel recruitment, all families residing in the German cities of Bonn and Cologne with children born between September 2003 and August 2004 were invited to join a mentoring program, along with one-third of families with children born between September 2002 and August 2003 ( $N = 14,451$ ). Parents were informed that, due to limited capacity, participation in the program could not be guaranteed. A total of 1,626 families expressed interest in participating and completed a brief questionnaire covering income, education, and whether both parents resided in the same household. The focus was on children whose parents met at least one of the following three criteria: (i) monthly household equivalence income below 1,065 euros, representing the 30th percentile of the German income distribution; (ii) neither parent holding a school-leaving qualification for university admission; or (iii) parents not residing together in the same household. All children meeting one of these criteria ( $N = 700$ ) and their parents were invited to a baseline interview held between September and October 2011. A total of 590 children and their parents attended the interview and provided written

consent for their address to be shared with the organization managing the mentoring program, constituting our primary sample. Out of this group, 212 children were randomly assigned to receive the intervention (“Low SES Treatment”), while the remaining 378 children served as the control group (“Low SES Control”). We used stratified random treatment assignment to ensure a proportional representation of all forms of pre-defined disadvantage (low income, low education, single parenthood) in the ITT group, while ensuring that the number of selected children matched the local supply of mentors.<sup>3</sup> The one-year mentoring intervention took place from October 2011 to January 2013.

Due to an unexpected mentor shortage during the intervention, 18% of children in the treatment group were unable to begin the mentoring program. An additional 8% had matches that did not proceed due to issues like mentor availability, including factors such as mentor relocations or pregnancies. Consequently, 74% of the treatment group received the intervention, and our analysis will focus on intention-to-treat estimates.

Additionally, some children whose parents did not meet any of the three selection criteria listed above were invited to join the panel ( $N = 150$  invited,  $N = 122$  completed the baseline interview and provided written consent). None of these children participated in the mentoring program. This “High SES control” group serves as an additional comparison group to be able to explore socioeconomic disparities. In later analysis we also rely on this sampling definition of high and low SES individuals.

Following the initial survey, the participating families are interviewed on a yearly basis (for details see Falk and Kosse, 2020, Kosse et al., 2020). The measures on digital skills were elicited in 2022, i.e., about ten years after the end of the mentoring program. At that time, the participants were 18 to 20 years old.

117 individuals from the treatment group, 226 of the control group and 92 of the high SES comparison group completed the survey on digital skills, i.e., the re-interviewing rate was about 61%. The re-interviewing rate does not differ between treatment and control group ( $p = 0.277$ , two-sample test of proportions). Our data also indicate that the sample is balanced regarding all key baseline characteristics, as can be seen in Table A3 in the appendix. To counteract minor imbalances, we use inverse probability weights in all main specifications in our analyses. The weights are constructed by, first, running a probit regression of participation in the year 2022 survey on key baseline characteristics (see Table A3) as well as the treatment

---

<sup>3</sup>The combination of the three forms of disadvantage and two regions yields fourteen strata. Given the larger relative supply of mentors in Bonn, we also assigned a higher share of children in Bonn to the ITT group. Thus, assignment into treatment was random conditional on region of residence. Therefore, we condition on strata fixed effects for the analyses of the treatment.

categories. Then, based on these estimates, we predict the probability of being in the year 2022 sample and use the inverse of the estimated probability as weights in our further estimations to account for minor imbalances due to attrition.

## 2.5 The treatment intervention

The mentoring program for primary-school-aged children, called “Balu und Du” (“Baloo and You”), pairs each child with a volunteer mentor—typically a university student aged 18 to 30—for a period of one year; a detailed description can be found in Müller-Kohlenberg and Drexler (2013). During the one-year treatment period, the participating children spend one afternoon each week with their mentor, participating in activities tailored to their individual needs and interests. These interactions might include visits to a zoo, museum, or playground, as well as cooking, crafting, or simply having a conversation. The goal is to provide children with meaningful social engagement outside the home, enhancing personal growth through supportive and varied experiences. The program is embedded in a structured support system, where mentors document their weekly activities in online diaries. Trained program coordinators review these diaries, provide feedback, and hold bi-weekly meetings with mentors to offer guidance and address any challenges. Since its inception in 2002, “Balu und Du” has facilitated over 18,000 mentor-child relationships across more than 150 locations in Germany, making it one of the country’s largest mentoring initiatives. Within the bfp, mentored children participated for an average of 9.3 months, meeting with their mentors 22.8 times (std. dev. 11.9), totaling approximately 92 hours of mentorship (Kosse et al., 2020).

The concept of the program is based on “informal learning”, which aims to integrate learning processes into everyday activities instead of focusing on academic achievements through, e.g., tutoring. As such, the program aims to strengthen basic skills and non-academic abilities. The new experiences provided by mentors enrich the social environment of the participants, creating fertile ground for the acquisition of new skills and abilities. According to Bandura (1977), both mastery and vicarious learning experiences play a crucial role in this process. Mastery experiences—successes achieved through one’s own efforts—directly reinforce self-efficacy, helping children build confidence in their abilities as they successfully accomplish tasks with their mentors (Bandura, 1977). Vicarious learning, where children observe and learn from their mentors’ actions, further supports skill acquisition by offering models of effective strategies and behaviors that children can emulate (Schunk, 1987). Together, these experiences should foster resilience, reinforce

a growth-oriented mindset, and enable children to feel more capable and motivated to acquire new skills also after the mentoring intervention concludes. This could therefore translate into increased levels of new skills as well as higher confidence in such skills.

### 3 Results

In this section, we proceed as follows: First, using the representative sample of the SOEP-IS, we provide descriptive evidence on the predictive power of both digital skill levels and confidence in digital skills for labor market success. Second, we examine social disparities within this representative sample. Third, we confirm the observed patterns of social disparities within the bfp dataset. Fourth, we present causal evidence on the impact of enriching the early social environment, based on the RCT. Finally, we offer results that shed light on the interpretation of the causal effects of the mentoring program.

#### 3.1 The predictive power for labor market success

We complement the existing literature on the relationship between digital skills and labor market success by providing the first direct evidence on the dual importance of both digital skill level and confidence in digital skills as predictors of labor market outcomes. In Table 1, we regress log hourly gross wages, our measure of labor market success, on digital skill levels and confidence in digital skills, controlling for age and gender. Using both predictors separately, columns 1 and 2 indicate substantial and very similar predictive power of both levels and confidence. Specifically, a one-standard-deviation increase in either skill level or confidence is associated with an approximately 10% increase in hourly wages ( $p < 0.01$  for both). These relationships also hold when both levels of digital skills and confidence in these skills are included in the same regression model, as shown in column 3. In this specification, a one-standard-deviation increase in skill levels or confidence is associated with a 7.5% increase in hourly wages ( $p < 0.01$  for both), highlighting the dual relevance of skill levels and confidence.

In additional analyses, we explore potential interactions and non-linearities in these effects. The non-significant interaction term of level and confidence in Table A4 suggests that the two factors do not interact in predicting wages. Further, in A5 we include squared terms for skill levels and confidence in the regression model. The significant negative coefficient for squared skill levels suggests a concave

relationship between skill levels and wages, while the non-significant coefficient for squared confidence implies a linear relationship between confidence and wages within the given support.

Table 1: Predictive Power of Digital Skills (Level & Confidence)

Sample: SOEP-IS	Log Hourly Gross Wage		
	(1)	(2)	(3)
Level of Digital Skills (standardized)	0.098*** (0.023)		0.074*** (0.024)
Confidence in Digital Skills (standardized)		0.097*** (0.022)	0.076*** (0.022)
Controls	Age, Age <sup>2</sup> , Gender		
Observations	938	938	938

*Notes:* The dependent variable is the log hourly gross wage. Coefficients are OLS estimates. Robust standard errors reported in parentheses. All regressions control for age, age squared and gender. Sample restricted to those who participate in the labor market. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### 3.2 Social disparities in a representative sample

Having established that both digital skill levels and confidence in digital skills are significant predictors of labor market success, we now turn to examining how these dimensions vary across different social groups. Specifically, we investigate gender and socioeconomic disparities in digital skills within our representative SOEP-IS sample. In a first step, we focus on social disparities regarding the level of digital skills. In Table 2 we regress the level of digital skills on parental SES and gender. Column 1 indicates a highly significant gender gap regarding the level of digital skills. On average, females compared to males indicate 27% of a standard deviation lower levels of digital skills ( $p < 0.01$ ). Parental SES is not significantly related to the level of digital skills. To examine whether there are gender-specific SES gaps we split the parental socioeconomic background variable by gender. Columns 2 and 3 present the estimates for males and females, respectively. For both, the estimate is small and insignificant.

In a second step, we focus on social disparities regarding confidence in digital skills. In Table 3 we regress confidence in digital skills on parental SES and gender. As for the level of digital skills, column 1 indicates a highly significant gender

Table 2: Level of Digital Skills by Parental SES and Gender

Sample: SOEP-IS	Level of Digital Skills (standardized)		
	(1)	(2)	(3)
	Full sample	Sample: Females	Sample: Males
Low Parental SES	-0.078 (0.053)	-0.031 (0.068)	-0.124 (0.081)
Female	-0.267*** (0.051)		
Observations	938	465	473

*Notes:* The dependent variable is the level of digital skills. Coefficients are OLS estimates. Robust standard errors reported in parentheses. All regressions control for age. For comparability, the sample is restricted to individuals that are active on the labor market. Low Parental SES is a dummy variable based on a median split of the parents' highest Treiman job prestige score. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

gap regarding confidence in digital skills. However, in contrast to levels, the results on confidence also indicate a significant SES difference. Individuals from low socioeconomic backgrounds indicate a 13% of a standard deviation ( $p < 0.05$ ) lower confidence in their digital skills compared to those from high socioeconomic backgrounds. The analysis of gender-specific gaps, in columns 2 and 3, indicates that the parental SES gap in confidence is largely driven by men. While for males, we find a pronounced and highly significant SES gap, for females the gaps are small and not statically significant. These patterns remain when controlling for digital skill levels, see Table A6.

Table 3: Confidence in Digital Skills by Parental SES and Gender

Sample: SOEP-IS	Confidence in Digital Skills (standardized)		
	(1)	(2)	(3)
	Full sample	Sample: Females	Sample: Males
Low Parental SES	-0.128** (0.055)	0.043 (0.073)	-0.296*** (0.082)
Female	-0.273*** (0.053)		
Observations	938	465	473

*Notes:* The dependent variable is confidence in digital skills. Coefficients are OLS estimates. Robust standard errors reported in parentheses. All regressions control for age. For comparability, the sample is restricted to individuals that are active on the labor market. Low Parental SES is a dummy variable based on a median split of the parents' highest Treiman job prestige score. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### 3.3 Social disparities: Causal evidence

In this section we examine the social disparities regarding digital skills in the Bonn Family Panel. For comparability with the previous results we use representative distributions to standardize our measures. As a starting point, we compare the descriptive gaps in the high and low SES control group sample of the bfp to the disparities in the representative SOEP-IS sample. Subsequently, we explore the causal effects of the early-childhood mentoring intervention on digital skills.

In line with the representative results based on the SOEP-IS, the bfp, which focuses exclusively on young adults, reveals the same pattern of social disparities. Both, for skill levels and confidence, we find highly significant gender gaps of comparable magnitude to those observed in the SOEP-IS (Table A7). Also, as before, we observe a parental SES gap only for confidence but not for skill levels and, again, the SES gap on confidence exists only for males but not for females (Table A8 and Figures 1 and 2).

In the following we present our main analyses: the effects of early mentoring on the level of digital skills and confidence in digital skills. The randomized controlled implementation of the intervention allows for a causal interpretation when comparing the low SES control and the low SES treatment groups. Figures 1 and 2 present these comparisons and reveal the following pattern: While there are no significant treatment effects in situations where there is no SES gap, there is a significant treatment effect in the situation where also an SES gap is present.<sup>4</sup> Specifically, the descriptive analyses of the SOEP-IS and the control groups of the bfp indicated a parental SES gap exclusively for males regarding confidence. This is exactly the group for which we find a sizable and significant treatment effect. Males in the treatment group are more than 30% of a standard deviation more confident regarding their digital skills compared to those in the control group ( $p = 0.015$ , see also Table A10). Interpreting the effects on confidence for females and males as a joint set of hypotheses and therefore calculating false discovery rate  $q$ -values confirms that the statistical significance is also not due to alpha-error inflation (for males:  $q = 0.031$ , for female:  $q = 0.825$ ).<sup>5</sup> A series of robustness checks indicates that the treatment effect patterns are independent of using IPW or controlling for the level of digital skills, see Tables A11, A12 and A13.

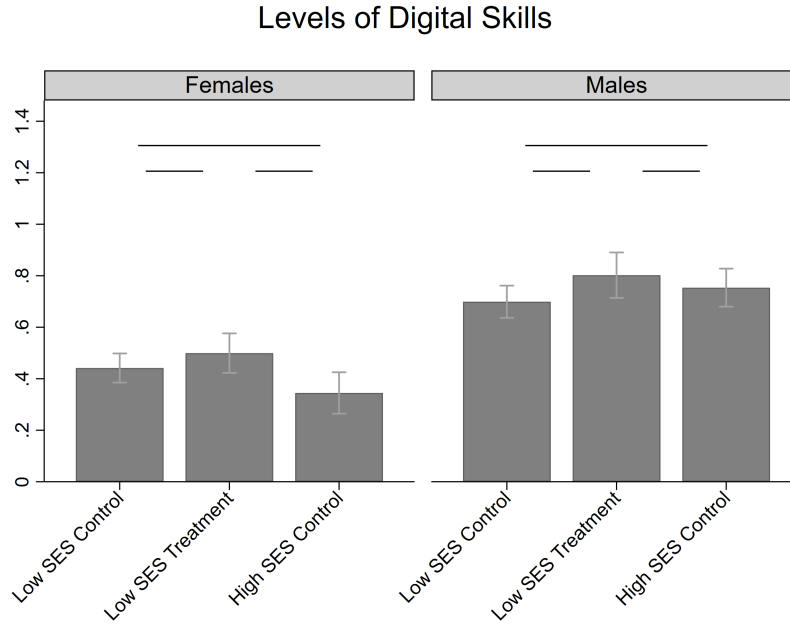
---

<sup>4</sup>This is a typical pattern in the literature on the effects of mentoring. For an overview see, e.g., Falk et al. (2023).

<sup>5</sup>False Discovery Rate  $q$ -values are sharpened two-stage  $q$ -values (Anderson, 2008, Benjamini et al., 2006).

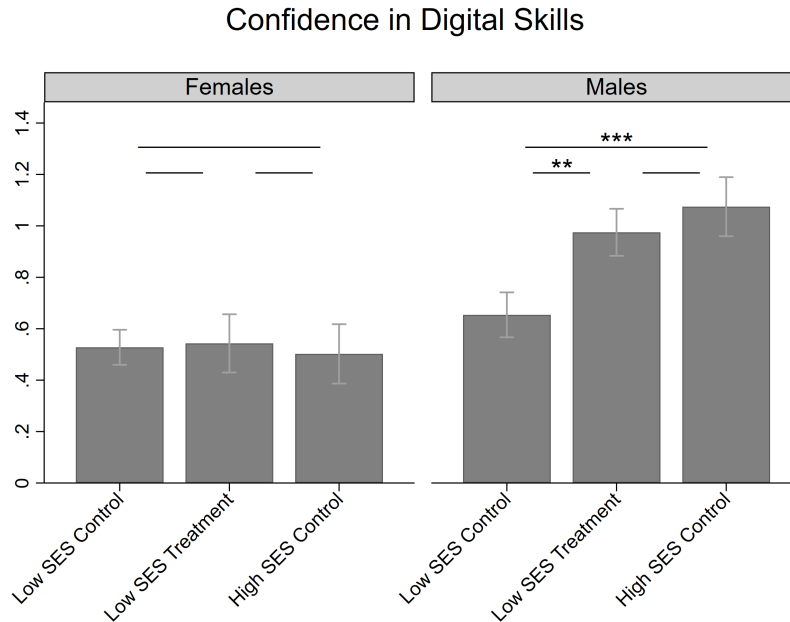


Figure 1: Level of Digital Skills in Treatment and Control Groups



*Notes:* The bars show the standardized level of digital skills (sample: bfp). The differences between the bars correspond to the estimates shown in Tables A8 and A9 (including strata fixed effects, using IPW). Error bars reflect robust standard errors. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Figure 2: Confidence in Digital Skills in Treatment and Control Groups



*Notes:* The bars show standardized confidence in digital skills (sample: bfp). The differences between the bars correspond to the estimates shown in Tables A8 and A10 (including strata fixed effects, using IPW). Error bars reflect robust standard errors. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

The fact that we find a significant treatment effect only in the presence of a parental SES effect suggests that the treatment is not increasing confidence in digital skills per se but in situations when the lower confidence is driven by the socioeconomic environment. This suggests that enriching the socioeconomic environment bears the potential to close SES gaps.

### 3.4 Interpretation of the treatment effect

In this section we further explore the treatment effect for males on confidence in digital skills. In a first step we explore if the treatment makes the participating males less *underconfident* or more *overconfident*. In a second step we explore to which degree the treatment effect on confidence is specific to digital skills.

#### 3.4.1 Less *underconfidence* vs. more *overconfidence*

In general, the average confidence level of a group can be increased either by reducing *underconfidence* or by increasing *overconfidence*. *Overconfidence* is a cognitive bias where individuals overestimate their abilities compared to objective reality. In contrast, *underconfidence* means that someone underestimates its abilities compared to objective reality. While some studies suggest that *overconfidence* can be beneficial in certain contexts (Bénabou and Tirole, 2002, Schwardmann and Van der Weele, 2019), it has been shown to lead to highly detrimental outcomes across various domains. These include individual investment decisions (Barber and Odean, 2000) or CEO behavior (Malmendier and Tate, 2005). Kahneman (2011) characterizes *overconfidence* as the most significant and impactful cognitive bias, referring to it as “the mother of all biases”.

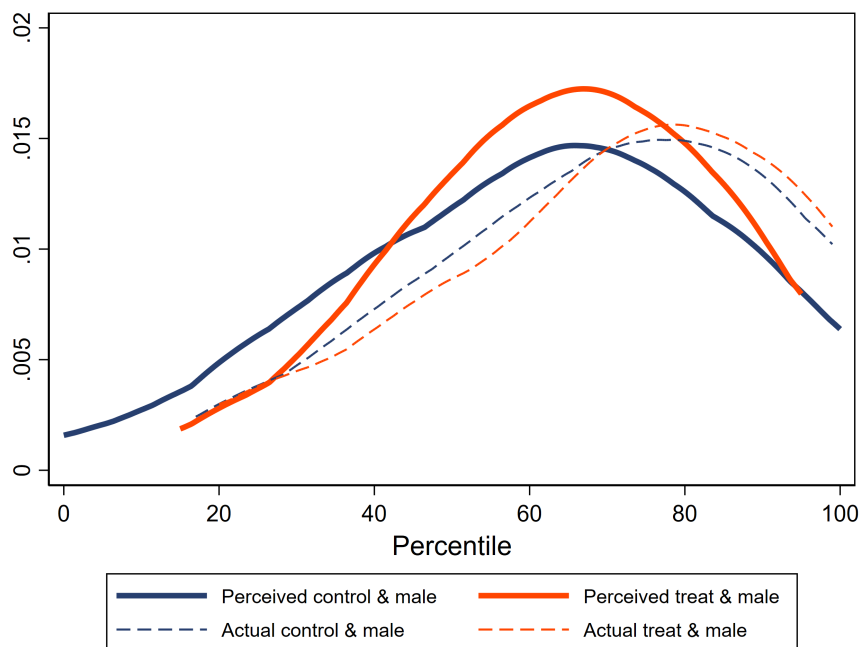
To investigate if the treatment makes the participating males less *underconfident* or more *overconfident*, in Figure 3, we compare the perceived and the actual positions in the representative distribution of digital skills for the low SES control and treatment groups. The blue lines refer to the control group, the orange lines refer to the treatment group. The solid lines refer to the perceived percentile (our measure of confidence), the dashed lines refer to the actual percentile in the representative distribution. The information about the representative distribution of digital skill levels stems from the SOEP-IS sample.

In line with the absence of a treatment effect on the level of digital skills (Tables A9 and A11), the actual percentiles in the representative distributions, indicated by the two dashed lines, are very close together for treatment and control group. A closer look at perceived percentiles (solid lines) provides two important insights:

First, the distribution of the perceived position in the treatment group compared to the control group shows less mass in the left tail,<sup>6</sup> more mass in the center but not more mass in the right tail. Second, even after the increase in the perceived position through the treatment, the distribution of the perceived position of the treatment group is still clearly left from the distribution of their actual position.

In sum, this analysis suggests that the treatment mainly increased the confidence in digital skills of participants with low confidence levels and, therefore, reduced the level of *underconfidence*. It did not increase *overconfidence* in digital skills in the sample of young male adults.

Figure 3: Confidence in Digital Skills - Distribution of Perceived vs. Actual Percentiles for Males in the bfp



*Notes:* This figure shows univariate kernel density estimates, Epanechnikov kernel, half-width of the kernel: 15. The displayed sample consists of the males from the low SES control and treatment groups. Actual percentiles were calculated using the full SOEP-IS sample.

### 3.4.2 Increased confidence in digital skills vs. improved general self-concept

An important question regarding the interpretation of the treatment effect is whether the treatment increased confidence specifically regarding digital skills or if it improved the individuals' self-concept on a more general level. In our setup this question is hard to address, as the scarce survey-time in the bfp prevented us from

<sup>6</sup>This is in line with the results of quantile regressions shown in Table A14 that indicate a pronounced treatment effect at the lower part of the distribution.

including directly comparable confidence tasks regarding other skills or measures on general self-concept. However, we can make use of the rich panel data of the bfp. In the years 2015 and 2016, i.e. three and four years after the end of the treatment, the extensively validated Single-Item Self-Esteem Scale (SISE)<sup>7</sup> was elicited. While this not a perfect measure of general self-concept, we argue that it serves as a good proxy: First, the personality psychological literature discusses, both, confidence and self-esteem as aspects of self-concept and indicates their theoretical and empirical relation (e.g., Rosenberg, 1965, Judge et al., 2002). Second, general self-esteem (as measured by the SISE) and confidence in digital skills indicate a sizable correlation in the sample under study. While the raw correlation between the score of the two self-esteem measures and confidence in digital skills is only 0.187, the measurement error corrected correlation using “obviously related IV” (ORIV) is 0.296 (Gillen et al., 2019).<sup>8</sup>

To explore to what degree the treatment effect on confidence in digital skills is driven by effects on general self-esteem, in Table 4, we repeat the main treatment effect regression but control for effects on general self-esteem. For comparison, column 1 shows the raw treatment effect without any further controls. In column 2 we condition on the score of the two self-esteem measures. As discussed above the self-esteem score is correlated with confidence in digital skills ( $p < 0.05$ ), however, it explains only about 8% ( $= (0.321 - 0.295)/0.321$ ) of the treatment effect on confidence in digital skills. Yet, if self-esteem is measured with noise, the specification in column 2 will not fully account for the potential treatment effect on general self-esteem. To properly control for the treatment effect on self-esteem in the presence of measurement error, we use the ORIV technique suggested by (Gillen et al., 2019). This approach eliminates the uncorrelated part of the measurement error in the self-esteem measures by using the two measures of self-esteem as instrument for each other. The results shown in column 3 are the second stage coefficients of this estimation. They indicate a pronounced relation between self-esteem and confidence in digital skill and indicate that the treatment effect on general self-esteem explains about 19% ( $((0.321-0.260)/0.321)$ ) of the treatment effect on confidence in digital skills. This implies that a non-negligible part of the treatment effect on con-

---

<sup>7</sup>We use the German translations that is also used in the SOEP (core sample): “Ich habe eine positive Einstellung zu mir selbst” (rated on a 7-point Likert-scale) which directly translates to “I have a positive attitude toward myself”.

<sup>8</sup>The 1-item self-esteem measures are probably prone to substantial measurement error which attenuates the correlation. However, the data structure of the two repeated self-esteem measure in two different years allows us to estimate the measurement error corrected ORIV correlation by using the two measures as instruments for each other. See Gillen et al. (2019) for detailed explanations and discussions.

fidence in digital skills is actually driven by more general effects on self-concept. However, the residual treatment effect on confidence in digital skills is still sizable and significant. This suggests that the treatment specifically increased confidence in the dynamic and fast developing domain of digital skills.

Table 4: ORIV Analysis of Self-Esteem on the Treatment Effect

Sample: bfp Low SES Males	Confidence in Digital Skills (standardized)		
	OLS (1)	OLS (2)	IV (3)
Treated	0.321** (0.131)	0.295** (0.130)	0.260** (0.131)
Self-esteem (standardized) (Average of 2015 & 2016)		0.181** (0.084)	
Self-esteem (standardized) (ORIV: 2015 & 2016)			0.395** (0.173)
Observations (cluster)	170	170	170

*Notes:* Columns 1 and 2 show OLS estimates using strata fixed effects and inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Column 3 shows second stage ORIV estimates using strata fixed effects and inverse probability weighting. Clustered standard errors reported in parentheses. The sample includes only males of the treatment & low SES control group. Standardization of the confidence measure was done using the moments from the representative SOEP-IS sample. Standardization of the other measures was done using the moment from the full bfp sample. Self-esteem (average) is the standardized mean of the standardized measures collected in 2015 and 2016 (Robins et al., 2001). The ORIV was estimated using the standardized self-esteem measures for the survey years 2015 and 2016 as instruments for each other. The sample in column 3 includes duplicated data due to the dataset expansion required for the ORIV analysis, therefore standard errors are clustered for this estimation. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## 4 Discussion and conclusion

This study uncovers novel insights regarding the determinants and consequences of digital skills in a rapidly evolving labor market. By leveraging a unique combination of representative survey data and causal evidence from a randomized controlled trial, we make three key contributions: (1) we document the labor market relevance of both digital skill levels and confidence in digital skills, (2) we reveal consistent pronounced social disparities in these dimensions, and (3) we provide first evidence that early-life interventions can at least partially ameliorate these disparities, particularly in digital confidence.

The dual importance of digital skills and confidence highlights the role of non-

cognitive attributes in labor market success. While technical digital proficiency is well-recognized as a key determinant of earnings, our findings demonstrate that confidence in these skills is equally predictive of wages. This underscores a complementarity between cognitive skills and non-cognitive skills in navigating also in technology-intensive labor markets. Policies aimed solely at improving digital proficiency may fall short if they neglect the role of confidence in skill acquisition, application, and signaling.

Moreover, our results suggest that social disparities in digital skills may amplify existing inequalities. Males from higher socioeconomic backgrounds, who already benefit from advantages in many labor market dimensions, also exhibit both higher skill levels and greater confidence, are better positioned to capitalize on technological change. This raises the possibility that technological transformations could exacerbate inequality in the absence of targeted interventions.

However, our study also provides initial evidence of partial malleability of these gaps through early interventions. Exploring the long-term effects of a childhood mentoring intervention suggests that early mentoring programs bear the potential to close parental background-driven confidence gaps in digital skills. The program persistently increased confidence in digital skills for males without making them overconfident. Only a minor share of this effect can be explained by changes in general self-concept and self-esteem, which suggests that the treatment specifically increased confidence in this dynamic and fast developing domain. While we do not find any effects of the intervention on the actual level of digital skills, this does obviously not preclude the possibility of persistently enhancing digital skills through other interventions at different development stages. For example, recent evidence suggests that coding bootcamps and digital fact-checking trainings can effectively increase the level of digital skills for disadvantages groups (Aramburu et al., 2021, Moore and Hancock, 2022). How schools and community programs in different cultures and societies could effectively incorporate digital skill trainings that build both competence and confidence is a highly relevant and timely question for future research.

## References

- Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, 40(1):7–72.
- Acemoglu, D., Autor, D. H., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1):293–340.
- Alekseeva, L., Azar, J., Gine, M., Samila, S., and Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71:293 – 340.
- Anderson, M. L. (2008). Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association*, 103(484):1481–1495.
- Aramburu, J., Goicoechea, A., and Mobarak, A. M. (2021). Coding Bootcamps for Female Digital Employment. World Bank Group Policy Research Working Paper No. 33021.
- Autor, D., Levy, F., and Murnane, R. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.
- Babina, T., Fedyk, A., He, A. X., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2):191–215.
- Barber, B. M. and Odean, T. (2000). Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance*, 55(2):773–806.
- Bénabou, R. and Tirole, J. (2002). Self-Confidence and Personal Motivation. *The Quarterly Journal of Economics*, 117(3):871–915.
- Benjamini, Y., Krieger, A. M., and Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3):491–507.

- Berger, E. M., Fehr, E., Hermes, H., Schunk, D., and Winkel, K. (2025). The Impact of Working Memory Training on Children’s Cognitive and Noncognitive Skills. *Journal of Political Economy*, forthcoming.
- Bick, A., Blandin, A., and Deming, D. J. (2024). The Rapid Adoption of Generative AI. NBER Working Paper No. 32966.
- Bonney, K., Breaux, C., Buffington, C., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., and Savage, K. (2024). Tracking Firm Use of AI in Real Time: A Snapshot from the Business Trends and Outlook Survey. NBER Working Paper No. 32319.
- Cappelen, A., List, J., Samek, A., and Tungodden, B. (2020). The Effect of Early-Childhood Education on Social Preferences. *Journal of Political Economy*, 128(7):2739–2758.
- Carvajal, D., Franco, C., and Isaksson, S. (2024). Will Artificial Intelligence Get in the Way of Achieving Gender Equality? NHH Dept. of Economics Discussion Paper No. 03.
- Coffman, K. B., Collis, M. R., and Kulkarni, L. (2024). Whether to Apply. *Management Science*, 70(7):4649–4669.
- Colombo, E., Mercurio, F., and Mezzanzanica, M. (2019). AI meets labor market: Exploring the link between automation and skills. *Information Economics and Policy*, 47:27–37.
- Dolan, P., Foy, C., Kavetsos, G., and Kudrna, L. (2021). Faster, Higher, Stronger... and Happier? Relative Achievement and Marginal Rank Effects. *Journal of Behavioral and Experimental Economics*, 95:104761.
- Eisfeldt, A. L. and Schubert, G. (2024). AI and Finance. NBER Working Paper No. 33076.
- Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702):1306–1308.
- Falck, O., Heimisch-Roecker, A., and Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, 50(7):104064.
- Falk, A. and Kosse, F. (2020). The briq family panel: An overview. mimeo.



- Falk, A., Kosse, F., and Pinger, P. (2025). Mentoring and schooling decisions: Causal evidence. *Journal of Political Economy*, forthcoming.
- Falk, A., Kosse, F., and Stötzer, L. S. (2023). Sozioökonomischer Status, Mentoring und Chancengerechtigkeit: Thünen-Vorlesung 2022. *Perspektiven der Wirtschaftspolitik*, 24(2):264–275.
- Gathmann, C., Kagerl, C., Pohlen, L., and Roth, D. (2024). The pandemic push: Digital technologies and workforce adjustments. *Labour Economics*, 89:102541.
- Gillen, B., Snowberg, E., and Yariv, L. (2019). Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study. *Journal of Political Economy*, 127(4):1826–1863.
- Goldfarb, A. and Prince, J. (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy*, 20(1):2–15.
- He, Q. and Kircher, P. (2023). Updating about Yourself by Learning about the Market: The Dynamics of Beliefs and Expectations in Job Search. NBER Working Paper No. 31940.
- Heckman, J. J. and Mosso, S. (2014). The Economics of Human Development and Social Mobility. *Annual Review of Economics*, 6(1):689–733.
- Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, 24(3):411–482.
- Helsper, E. J., Schneider, L. S., van Deursen, A. J., and van Laar, E. (2020). The youth Digital Skills Indicator: Report on the conceptualisation and development of the ySKILLS digital skills measure. *KU Leuven, Leuven: ySKILLS*.
- Horn, S. and Loewenstein, G. (2021). Underestimating Learning by Doing. SSRN Working Paper No. 3941441.
- Humlum, A. and Meyer, B. B. (2022). Artificial Intelligence and College Majors. Rockwool Foundation Research Unit Study Paper No. 172.
- Humlum, A. and Vestergaard, E. (2024). The Adoption of ChatGPT. *Becker Friedman Institute for Economics Working Paper No. 2024-50*.

- James, J. (2007). From origins to implications: Key aspects in the debate over the digital divide. *Journal of Information Technology*, 22(3):284–295.
- Judge, T. A., Erez, A., Bono, J. E., and Thoresen, C. J. (2002). The Core Self-Evaluations Scale: Development of a Measure. *Personnel Psychology*, 55(1):69–98.
- Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux, New York.
- Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H., and Falk, A. (2020). The Formation of Prosociality: Causal Evidence on the Role of Social Environment. *Journal of Political Economy*, 128(2):434–467.
- Malmendier, U. and Tate, G. (2005). CEO Overconfidence and Corporate Investment. *The Journal of Finance*, 60(6):2661–2700.
- McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., and Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2):375–415.
- Moore, R. C. and Hancock, J. T. (2022). A digital media literacy intervention for older adults improves resilience to fake news. *Scientific Reports*, 12.
- Müller-Kohlenberg, H. and Drexler, S. (2013). Balu und Du (“Baloo and You”)-A Mentoring Program: Conception and Evaluation Results. *Mentoring: Practices, Potential Challenges and Benefits*.
- Nelson, R. R. and Phelps, E. S. (1966). Investment in Humans, Technological Diffusion, and Economic Growth. *The American Economic Review*, 56(1/2):69–75.
- Resnjanskij, S., Ruhose, J., Wiederhold, S., Woessmann, L., and Wedel, K. (2024). Can Mentoring Alleviate Family Disadvantage in Adolescence? A Field Experiment to Improve Labor Market Prospects. *Journal of Political Economy*, 132(3):1013–1062.
- Richter, D. and Schupp, J. (2012). SOEP Innovation Sample (SOEP-IS) — Description, Structure and Documentation. SOEPpapers on Multidisciplinary Panel Data Research No. 463.
- Robins, R. W., Hendin, H. M., and Trzesniewski, K. H. (2001). Measuring Global Self-Esteem: Construct Validation of a Single-Item Measure and the Rosenberg Self-Esteem Scale. *Personality and Social Psychology Bulletin*, 27(2):151–161.

- Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5):71–102.
- Rosenberg, M. (1965). *Society and the Adolescent Self-Image*. Princeton University Press.
- Saka, O., Eichengreen, B. J., and Aksoy, C. G. (2021). Epidemic Exposure, Fintech Adoption, and the Digital Divide. NBER Working Paper No. 29006.
- Schunk, D., Berger, E. M., Hermes, H., Winkel, K., and Fehr, E. (2022). Teaching self-regulation. *Nature Human Behaviour*, 6(12):1680–1690.
- Schunk, D. H. (1987). Peer Models and Children’s Behavioral Change. *Review of Educational Research*, 57(2):149–174.
- Schwardmann, P. and Van der Weele, J. (2019). Deception and Self-Deception. *Nature Human Behaviour*, 3(10):1055–1061.
- Sorrenti, G., Zölitz, U., Ribeaud, D., and Eisner, M. (2025). The Causal Impact of Socio-Emotional Skills Training on Educational Success. *Review of Economic Studies*, forthcoming.
- Treiman, D. J. (2013). *Occupational Prestige in Comparative Perspective*. Academic Press, New York.
- Werner, K. and Woessmann, L. (2023). The Legacy of COVID-19 in Education. *Economic Policy*, 38(115):609–668.

## Additional tables

Table A1: Digital Skills - Item Wording (English)

Questionnaire Items (examples) (13 items in total)
<i>Technical and operational skills:</i> I know how to adjust privacy settings. I know how to turn off the location settings on mobile devices. I know how to protect a device (e.g., with a PIN). I know how to store photos, documents, or other files in the cloud (e.g., Google Drive, iCloud). I know how to use private browsing (e.g., incognito mode). I know how to block unwanted pop-up messages or ads.
<i>Programming:</i> I know how to use programming languages (e.g., XML, Python, Java, C++).
<i>Information navigation and processing:</i> I know how to choose the best keywords for online searches. I know how to find a website I have visited before. I know how to find information on a website, no matter how it is designed. I know how to figure out if a website can be trusted. I know how to use advanced search functions in search engines. I know how to check if the information I find online is true.
Scale: “strongly disagree”, “disagree”, “neutral”, “agree”, “strongly agree”, “I don’t know”, “Prefer not to say”

Table A2: Digital Skills - Item Wording (German)

Questionnaire Items (examples) (13 items in total)
<p><i>Anwendungs- und technologische Fähigkeiten:</i></p> <p>Ich weiß, wie man Datenschutzeinstellungen anpasst.</p> <p>Ich weiß, wie man den Standort auf mobilen Geräten ausschaltet.</p> <p>Ich weiß, wie man ein Gerät schützt (z.B. mit PIN, Bildschirmmuster, Fingerabdruck oder Gesichtserkennung).</p> <p>Ich weiß, wie man Fotos, Dokumente oder andere Dateien in einer Cloud speichert (z.B. Google Drive, iCloud).</p> <p>Ich weiß, wie man privates Surfen einstellt.</p> <p>Ich weiß, wie man unerwünschte Pop-Up-Nachrichten oder Anzeigen blockiert.</p>
<p><i>Programmieren:</i></p> <p>Ich kann eine Programmiersprache (z.B. XML, Python, Java, C++) anwenden.</p>
<p><i>Information und Navigation:</i></p> <p>Ich weiß, welche Stichwörter man am besten bei einer Internet-Suche wählt/eingibt.</p> <p>Ich weiß, wie ich eine Webseite wiederfinde, die ich bereits besucht habe.</p> <p>Ich weiß, wie ich Informationen auf einer Webseite finde, egal wie sie aufgebaut ist.</p> <p>Ich weiß, wie ich herausfinde, ob eine Webseite vertrauenswürdig ist.</p> <p>Ich weiß, wie man erweiterte Suchfunktionen in Suchmaschinen verwendet.</p> <p>Ich weiß, wie ich überprüfen kann, ob die im Internet gefundenen Informationen wahr sind.</p>
<p>Skala: "Trifft überhaupt nicht zu", "Trifft eher nicht zu", "Trifft teils zu und teils nicht zu", "Trifft eher zu", "Trifft voll und ganz zu", "Ich weiß nicht, was damit gemeint ist", "Das möchte ich nicht sagen"</p>

Table A3: Baseline Balance in the Follow-Up Sample ( $N = 343$ )

Baseline measure	Mean Control Group	Mean Treatment Group	Difference p-value
<b>Family characteristics:</b>			
Low parental income (binary)	0.470 (0.033)	0.410 (0.045)	0.285
Low parental education (binary)	0.435 (0.033)	0.459 (0.045)	0.664
Single parent (binary)	0.465 (0.033)	0.508 (0.045)	0.444
Number of siblings	1.287 (0.060)	1.202 (0.083)	0.445
Mother's age (in years)	38.888 (0.388)	39.233 (0.499)	0.596
<b>Child characteristics:</b>			
Female (binary)	0.504 (0.033)	0.484 (0.045)	0.712
Age (in years, at follow-up)	19.522 (0.037)	19.426 (0.052)	0.131

*Notes:* The values in columns 1 and 2 are means in control and treatment group. Standard errors are in parentheses. Measures are collected at baseline. Column 3 lists p-values of t-tests on the null hypothesis that the difference in means between treatment and control group are zero.

Table A4: Mincer Regression on Hourly Gross Wage - Interaction

Sample: SOEP-IS	Log Hourly Gross Wage			
	(1)	(2)	(3)	(4)
Level of Digital Skills (standardized)	0.098*** (0.023)		0.074*** (0.024)	0.073*** (0.024)
Confidence in Digital Skills (standardized)		0.097*** (0.022)	0.076*** (0.022)	0.086*** (0.025)
Digital Skills $\times$ Confidence				-0.025 (0.022)
Controls	Age, Age <sup>2</sup> , Gender			
Observations	938	938	938	938

*Notes:* The dependent variable is the log hourly gross wage. Coefficients are OLS estimates. Robust standard errors reported in parentheses. All regressions control for age, age squared and gender. Sample restricted to those who participate in the labor market. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table A5: Mincer Regression on Hourly Gross Wage - Squared Predictors

Sample: SOEP-IS	[Log.] Hourly Gross Wage				
	(1)	(2)	(3)	(4)	(5)
Confidence in Digital Skills	0.097*** (0.022)	0.093*** (0.024)	0.076*** (0.022)	0.073*** (0.024)	0.078*** (0.023)
Confidence in Digital Skills <sup>2</sup>		0.009 (0.018)		0.008 (0.018)	
Level of Digital Skills			0.074*** (0.024)	0.073*** (0.024)	0.081*** (0.024)
Level of Digital Skills <sup>2</sup>					-0.047** (0.018)
Controls	Age, Age <sup>2</sup> , Gender				
Observations	938	938	938	938	938

*Notes:* The dependent variable is the log hourly gross wage. Coefficients are OLS estimates. Robust standard errors reported in parentheses. All regressions control for age, age squared and gender. Sample restricted to those who participate in the labor market. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table A6: Confidence in Digital Skills by Parental SES and Gender with Digital Skills Control

Sample: SOEP-IS	Confidence in Digital Skills (standardized)		
	(1)	(2)	(3)
	Full sample	Sample: Females	Sample: Males
Low Parental SES	-0.104** (0.053)	0.048 (0.072)	-0.245*** (0.075)
Female	-0.189*** (0.051)		
Observations	938	465	473

*Notes:* This table shows OLS estimates. Robust standard errors reported in parentheses. For comparability, the sample is restricted to individuals that are active on the labor market. All regressions control for age and the actual digital skills of the individuals. Low Parental SES is a dummy variable based on a median split of the parents' highest Treiman job prestige score.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A7: Level of Digital Skills and Confidence by Parental SES and Gender

Sample: bfp	[Std.] Level of DS	[Std.] Confidence in DS
Control groups	(1)	(2)
Low Parental SES (Dummy)	0.020 (0.070)	-0.201* (0.103)
Female	-0.295*** (0.070)	-0.238** (0.101)
Observations	318	318

*Notes:* This table shows OLS estimates using inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Sample includes high & low SES control group. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .



Table A8: Parental SES Gaps in Digital Skills (Level &amp; Confidence) by Gender

Sample: bfp	[Std.] Level of DS		[Std.] Confidence in DS	
	(1)	(2)	(3)	(4)
	Sample: Female	Sample: Male	Sample: Female	Sample: Male
Control groups				
Low Parental SES (Dummy)	0.097 (0.098)	-0.055 (0.099)	0.026 (0.136)	-0.421*** (0.151)
Observations	161	157	161	157

*Notes:* This table shows OLS estimates using inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Sample includes high & low SES control group. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A9: Treatment Effect on the Level of Digital Skills using IPW

Sample: bfp	Level of Digital Skills (standardized)		
	(1)	(2)	(3)
	Full Sample	Sample: Female	Sample: Male
Low SES			
Treated	0.089 (0.081)	0.058 (0.104)	0.103 (0.123)
Observations	343	173	170

*Notes:* This table shows OLS estimates using strata fixed effects and inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Sample only includes the low SES Control and Treatment groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A10: Treatment Effect on Confidence in Digital Skills using IPW

Sample: bfp	Confidence in Digital Skills (standardized)		
	(1)	(2)	(3)
	Full Sample	Sample: Female	Sample: Male
Low SES			
Treated	0.135 (0.093)	0.015 (0.127)	0.321** (0.131)
Observations	343	173	170

*Notes:* This table shows OLS estimates using strata fixed effects and inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Sample only includes the low SES Control and Treatment groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A11: Treatment Effect on the Level of Digital Skills without IPW

Sample: bfp	Level of Digital Skills (standardized)		
Low SES	(1)	(2)	(3)
	Full Sample	Sample: Female	Sample: Male
Treated	0.073 (0.077)	0.086 (0.100)	0.068 (0.119)
Observations	343	173	170

*Notes:* This table shows OLS estimates using strata fixed effects (see section 2.4). Robust standard errors reported in parentheses. Sample only includes the low SES Control and Treatment groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A12: Treatment Effect on Confidence in Digital Skills without IPW

Sample: bfp	Confidence in Digital Skills (standardized)		
Low SES	(1)	(2)	(3)
	Full Sample	Sample: Female	Sample: Male
Treated	0.103 (0.091)	0.021 (0.130)	0.258** (0.129)
Observations	343	173	170

*Notes:* This table shows OLS estimates using strata fixed effects (see section 2.4). Robust standard errors reported in parentheses. Sample only includes the low SES Control and Treatment groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A13: Treatment Effect on Confidence in Digital Skills Controlling for Level of Digital Skills

Sample: bfp Low SES	Confidence in Digital Skills (standardized)		
	(1) Full Sample	(2) Sample: Female	(3) Sample: Male
Treated	0.113 (0.092)	0.010 (0.126)	0.291** (0.129)
Level of Digital Skills (standardized)	0.251*** (0.068)	0.094 (0.099)	0.291*** (0.103)
Observations	343	173	170

*Notes:* This table shows OLS estimates using strata fixed effects and inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. Sample only includes the low SES Control and Treatment groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table A14: Heterogeneity in Treatment Effect on Confidence Levels - Quantile Regression

Sample: bfp Low SES Males	Confidence in Digital Skills (standardized)			
	20th Quantile	40th Quantile	60th Quantile	80th Quantile
Treated	0.582*** (0.186)	0.374** (0.172)	0.125 (0.153)	-0.042 (0.154)
Observations	170	170	170	170

*Notes:* This table shows quantile regression estimates using strata fixed effects and inverse probability weighting (see section 2.4). Robust standard errors reported in parentheses. The sample includes only males of the low SES treatment and control groups. Standardization was done using the moments from the representative SOEP-IS sample.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .