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The future of employment revisited: how model selection affects digitization risks

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Abstract
The uniqueness of human labour is at question in times of smart technologies. As computing power and data available increases, the discussion on technological unemployment reawakens. Prominently, Frey and Osborne (Technol Forecast Soc Change 114:254–280, 2017) estimated that half of US employment must be considered exposed to computerization within the next 20 years; followed by a series of papers expanding the research with information on heterogeneous job-specific tasks within the same jobs diminishing digitization potentials to only smaller fractions of workers at high risk. The main contribution of our work is to show that the diversity of previous findings regarding the degree of digitization is additionally driven by model selection. For our case study, we consult experts in machine learning and industry professionals on the susceptibility to digital technologies in the Austrian labour market. Our results indicate that, while clerical computer-based routine jobs are likely to change in the next decade, professional activities, such as the processing of complex information, are less prone to digital change.

Keywords Classification · Employment · GLM · Technological change

JEL Classification E24 · J24 · J31 · J62 · O33

1 Introduction

The motivation behind our work is the discussion about technological unemployment. Nordhaus (2007) has pointed out that the improvements in computing power over the last twenty years have enabled technical devices to perform tasks in real

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world applications. Hence, they bring the discussion of technological unemployment back on the political agenda. Acemoglu and Restrepo (2020) calculate that an increased use of robots in the US economy between 1990 and 2007 had a negative effect on the labour market. According to their calculations, an increase in the number of industrial robots by one, per 1000 people employed, reduces the employment-to-population ratio by 0.18 to 0.34 percentage points.

In the past, machines have both complemented and competed with human labour. Inventive ideas and creative destruction, as Schumpeter (1942) puts it, have competed with powerful social and economic interest over the technological status quo. Various movements, such as the *Luddites*, who destroyed new machinery in the eighteenth century textile industry, have tried to deter progress in times of rising unemployment. However, the *Luddite fallacy* has found its way into the literature, as employment has not been eradicated alongside fast technological development, but instead continued to expand. Rather than eliminating human labour as such, technological advancements have changed a number of work profiles and led to the creation of new professions.

Nonetheless, technological development in recent history has often been linked to a displacement in specific professions (Bresnahan 1999) or even entire industries (Charles et al. 2013; Jaimovich and Siu 2012). According to Goldin and Katz (1998), technological progress led to the simplification of work processes in the nineteenth century. A combination of machines and unskilled labour substituted skilled labour and decreased demand in terms of skills. However, as technologies improved, technological job displacement shifted away from skilled to unskilled labour.

Similar to the competition between humans and robots for physical work, McAfee and Brynjolfsson (2014) emphasize that computerization has now started challenging human performance even in cognitive tasks. Beaudry et al. (2016), in an empirical analysis, find evidence that the demand for skilled labour has been declining in recent years. This is an indication that skills under pressure of substitution are altering as technological progress persists. Autor and Dorn (2013) show that the implementation of computer-based technologies has put pressure on wages. As routine tasks are increasingly automated, displaced workers reallocate to the lower skilled service sector with deteriorating wages. According to Goos et al. (2009), this has resulted in the increased polarization of the labour market in a number of developed economies (see also Dustmann et al. 2009). Increasing demand for well-paid jobs in which non-routine cognitive tasks are performed, as well as non-routine manual work at the lower end of the income distribution, in combination with the digitization of repetitive cognitive skills, is forcing employment away from the middle of the income distribution (see also Autor et al. 2003; Autor 2013; Michaels et al. 2014).

Recent publications, such as Ford (2015), raise concerns that “this time it could be different” and there will be no room for creating new jobs. Technological mass unemployment has been proclaimed many times throughout history (Mokyr et al. 2015). Nevertheless, to date, technological advancement has not caused mass unemployment. We have seen a shift in labour from the agricultural sector to manufacturing branches, and further into the service sector (Autor 2015). Overall employment has been steadily increasing worldwide, despite (or perhaps because of) technological progress. Hence, new technologies display two opposite effects on employment (Aghion and Howitt 1994): On the one hand, technologies substitute human labour in order to decrease production costs and increase productivity. This displacement effect lowers employment. On the other hand, reduced production costs increase real income and hence demand. The latter effect fosters production and demand for labour.

Frey and Osborne (2017) set the starting point for a series of papers that attempt to estimate the degree of susceptibility to digitization in the labour market. Addressing previous limitations, we assume that a significant share of the strong differences in the results between Frey and Osborne (2017) and follow-up studies is not only due to (a) task-heterogeneity of workers within the same occupation but also (b) due to model selection. As a case study, our investigation examines the degree of future digitization of job profiles in Austria. We link expert opinions with individual data from the OECD's PIAAC[1] data, which in turn allow for heterogeneity among workers within the same occupation. Our results confirm that a) an analysis at the job level instead of the occupational level decreases probabilities but also indicate that b) models with a binary outcome, as applied by Frey and Osborne (2017), result in a much higher share of jobs at risk than models with a fractional dependent variable, as used by Arntz et al. (2016)—even when controlling for varying tasks within the same occupation. In both settings, clerical computer-based routine jobs are likely to change in the next decade. Professional activities with the processing of complex information are less prone to digital change. The following Sect. 2 discusses the related research, while Sect. 3 describes the methodology and data used in this paper. Section 4 presents and discusses the results before the last section concludes the paper.

2 Literature review

The debate about the susceptibility of human labour to digital technologies accelerated since a prominent study by Frey and Osborne (2017). They were the first to attempt to quantify the potential of computer-based job displacement in the near future. Based on the estimates of robotic experts, the authors calculated the susceptibility to computerization of different jobs, according to the O*NET database in the US. They conclude that 47% of the jobs in the US are exposed to digitization (i. e. > 70% probability that the job could technically be replaced due to computerization within the next 20 years), which—if realized—would impose a sizeable threat to societal stability.

The estimates of Frey and Osborne (2017) have been the basis for several follow-up studies which confirmed that large shares of the labour force also in other economic regions perform tasks that could to a large extent be executed by computers (Bowles 2014; Pajarinen et al. 2014). Bowles (2014) applies the same method and transfers the results to European economies using the differences in the sectoral structure of each country. He concludes that 54% of jobs in Austria are at high risk

[1] PIAAC stands for Programme for the International Assessment of Adult Competencies.

of being displaced by computers. Similarly, Pajarinen et al. (2014) calculate a share of Finnish jobs at risk of 36%.

On the other hand, a string of research infers that the share of jobs at risk is in fact much smaller (Arntz et al. 2016; Bonin et al. 2015; Nagl et al. 2017; Nedelkoska and Quintini 2018). Arntz et al. (2016) emphasize that the method used by Frey and Osborne (2017) overstates the share of jobs susceptible to computerization. While Frey and Osborne (2017) do allow for heterogeneity in tasks *between* different jobs, they do not allow for alterations in the tasks *within* one occupation. According to Arntz et al. (2016), Arntz et al. (2017), Arntz et al. (2020) and Nedelkoska and Quintini (2018), one profession may contain different sets of tasks, and thus the risk of computerization could vary within this profession. Using PIAAC survey data, Arntz et al. (2016) transfer the original jobs by Frey and Osborne (2017) into the International Standard Classification of Occupations (ISCO) and combine information about the composition of tasks within each job profile with information from robotic experts on the susceptibility of jobs for the US labour market. They further transfer the results to other OECD member countries, indicating that only 9% of US workers and only 12% of Austrian workers are exposed to digitization.[2] Among OECD countries, Austria and Germany display the highest shares of the workforce at a high risk.

Nedelkoska and Quintini (2018) make use of a more detailed PIAAC data set (ISCO 4-digit level) for the Canadian economy in order to reduce the problem of transferring the original O*NET data by Frey and Osborne (2017) to an international classification. Once they calculated the relationship between the engineering bottlenecks and the risk of automation using only Canadian data, the estimation coefficients are used to calculate the risk of digitization of jobs beyond the original 70 occupations and outside Canada. They confirm the finding of low computerization risks in the US at 10% using detailed information on the 440 ISCO occupations.

Pouliakas (2018) show that lower probabilities do not depend on the PIAAC data set deployed. Using information from the European Skills and Jobs Survey instead, they find 14% of workers within the European Union to be at high risk.

The aforementioned studies for Europe are based on the Frey and Osborne (2017) data. For the German labour market, Dengler and Matthes (2015) relate the risk of digitization from the BERUFENET-Database to the tasks that are characteristic of each profession. They compute the share of tasks that can be classified as routine based, according to the classification by Spitz-Oener (2006). According to their findings, 15% of German workers are employed in jobs with a high risk of automation. Until now, there has been no piece of research for the Austrian labor market that has analysed the impact of digitization on the labour market by using newly collected data from European countries. In doing so, we correct the shortcomings in transferring the original US data (O*NET) by Frey and Osborne (2017) to ISCO. We also adjust for regional particularities in European labour markets, for example, differences in regulation or cultural particularities. Even though technological innovations have become market-ready, European customers might be more hesitant to

[2] Bonin et al. (2015) use a similar approach for Germany, and Nagl et al. (2017) for the Austrian economy. According to Nagl et al. (2017), 9% of Austrian workers are exposed to digitization.

substitute them for human interaction. In addition, we analyse the possibility of a non-linear relationship between education and future digitization, since both low- and high-skilled jobs are assumed to be less affected by digital technologies than medium-skilled professions (Dustmann et al. 2009).

Our work examines the reason for the stark diversity in previous findings about job digitization potentials. We propose that differences in the degree of susceptibility emerge not only from (a) whether tasks differ between or also within occupations but also (b) from model selection. In order to test this assumption, we conduct a case study similar to Frey and Osborne (2017) with a survey among Austrian research and industry experts. Our model testing confirms that differences in previous findings on the digitization of jobs are not only driven by heterogeneity among tasks within occupations (a) but also by the design of the model (b). Our results indicate that, while clerical computer-based routine jobs are likely to change in the next decade, professional activities, such as the processing of complex information, are less prone to digital change.

3 Data and methods

Frey and Osborne (2017) collected their data set during an expert workshop which was held in 2013 at the Oxford University's Engineering Sciences Department. It included 70 machine learning experts (Brandes and Wattenhofer 2016). Together with their team of experts, Frey and Osborne (2017) initially labelled 70 out of 703 US jobs concerning their susceptibility to computerization. They yielded binary labels which were then used to predict risks of digitization for all US professions.

Similar to the approach by Frey and Osborne (2017), we build our analysis upon expert opinions. Between 7th December 2017 and 7th January 2018, we consulted Austrian industry experts and academics in machine learning. Both groups were individually requested to participate in an online survey. The project was initially presented to the—at the time—most popular Vienna based meetups in the field of data science, machine learning and deep learning.[3] The online survey was then free to be distributed among individuals of related peer-groups; hence, the selection of experts worked via snowballing. Additionally, representatives of leading Austrian companies were approached to fill in their expertise. The final data set contains 35 individual expert opinions of which 14 stem from representatives of Austrian companies; 21 responses were from experts and academics in machine learning and AI.

The participants in our survey were asked about their opinion on the most common professions in Austria, as listed in Table 1. We asked our experts: *"Do you think that the tasks, which are characteristic of this profession today, will be substituted, to a significant degree within the next 10 years, by algorithmic technologies (such as machine learning, computer vision and natural language processing) or mobile robotics?" (Yes=1/No=0)*. This question analyses the degree to which the nature of certain professions is going to change due to technological advancement. Answers to this question do not necessarily reflect the risk of

[3] *Vienna Deep Learning Meetup* and *Vienna Data Science Group Meetup*.

Table 1 Our experts gave their yes/no responses in relation to the most common professions in Austria

ISCO-08-4 code	ISCO-08-4 name	Mean	Mode	*Consensus*
5311	Childcare workers	0.033	0	0
5120	Cooks	0.034	0	0
3255	Physiotherapy technicians and assistants	0.038	0	0
2652	Musicians, singers and composers	0.067	0	0
5141	Hairdressers	0.067	0	0
3412	Social work associate professionals	0.071	0	0
5412	Police officers	0.071	0	0
2341	Primary school teachers	0.074	0	0
2635	Social work and counselling professionals	0.103	0	0
3355	Police inspectors and detectives	0.103	0	0
5321	Healthcare assistants	0.103	0	0
6113	Gardeners, horticultural and nursery growers	0.111	0	0
2161	Building architects	0.148	0	0
6130	Mixed crop and animal producers	0.148	0	0
7421	Electronics mechanics and servicers	0.160	0	0
2212	Specialist medical practitioners	0.172	0	0
2310	University and higher education teachers	0.172	0	0
5131	Waiters	0.179	0	0
7126	Plumbers and pipe fitters	0.179	0	0
7512	Bakers, pastry cooks and confectionery makers	0.185	0	0
1349	Professional services managers not elsewhere classified	0.192	0	0
7412	Electrical mechanics and fitters	0.200	0	0
1323	Construction managers	0.207	0	0
1411	Hotel managers	0.207	0	0
3221	Nursing associate professionals	0.222	0	0
2330	Secondary education teachers	0.231	0	0
7411	Building and related electricians	0.240	0	0
3259	Health associate professionals not elsewhere classified	0.250	0	0
5151	Cleaning/housekeeping supervisors in offices, hotels and others	0.250	0	0
2142	Civil engineers	0.259	0	–
2149	Engineering professionals not elsewhere classified	0.261	0	–
2642	Journalists	0.267	0	–
1321	Manufacturing managers	0.286	0	–
2611	Lawyers	0.296	0	–
2359	Teaching professionals not elsewhere classified	0.304	0	–
2144	Mechanical engineers	0.308	0	–
3251	Dental assistants and therapists	0.321	0	–
3411	Police inspectors and detectives	0.321	0	–
3256	Medical assistants	0.333	0	–
2166	Graphic and multimedia designers	0.345	0	–
2631	Economists	0.346	0	–

Table 1 (continued)

ISCO-08-4 code	ISCO-08-4 name	Mean	Mode	*Consensus*
7233	Agricultural and industrial machinery mechanics and repairers	0.346	0	–
7522	Cabinet makers and related workers	0.348	0	–
2512	Software developers	0.357	0	–
5414	Security guards	0.357	0	–
9112	Cleaners and helpers in offices, hotels and other establishments	0.357	0	–
7119	Building frame and related trades workers not elsewhere classified	0.360	0	–
2421	Management and organization analysts	0.370	0	–
5153	Building caretakers	0.370	0	–
7112	Bricklayers and related workers	0.370	0	–
9412	Kitchen helpers	0.385	0	–
3257	Environmental and occupational health inspectors and associates	0.400	0	–
7231	Motor vehicle mechanics and repairers	0.400	0	–
2431	Advertising and marketing professionals	0.407	0	–
7212	Welders and flame cutters	0.407	0	–
1324	Supply, distribution and related managers	0.414	0	–
3359	Regulatory government associate professionals	0.423	0	–
5223	Shop sales assistants	0.423	0	–
7543	Product graders and testers (excluding foods and beverages)	0.458	0	–
3115	Mechanical engineering technicians	0.462	0	–
2262	Pharmacists	0.500	0	–
9629	Elementary workers not elsewhere classified	0.500	0	–
7214	Structural metal preparers and erectors	0.520	1	–
7523	Woodworking machine tool setters and operators	0.520	1	–
8219	Assemblers not elsewhere classified	0.538	1	–
3353	Government social benefits officials	0.556	1	–
3352	Government tax and excise officials	0.571	1	–
8212	Electrical and electronic equipment assemblers	0.577	1	–
9332	Drivers of animal-drawn vehicles and machinery	0.577	1	–
7223	Metal working machine tool setters and operators	0.583	1	–
3322	Commercial sales representatives	0.593	1	–
3323	Buyers	0.593	1	–
3334	Real estate agents and property managers	0.607	1	–
4120	Secretaries (general)	0.607	1	–
2411	Accountants	0.633	1	–
7321	Pre-press technicians	0.640	1	–
9329	Manufacturing labourers not elsewhere classified	0.640	1	–
9333	Freight handlers	0.652	1	–
8160	Food and related products machine operators	0.667	1	–

Table 1 (continued)

ISCO-08-4 code	ISCO-08-4 name	Mean	Mode	*Consensus*
9334	Shelf fillers	0.692	1	–
9621	Messengers, package deliverers and luggage porters	0.692	1	–
3118	Draughtspersons	0.720	1	–
3313	Accounting associate professionals	0.731	1	–
4110	General office clerks	0.750	1	1
8322	Car, taxi and van drivers	0.759	1	1
8131	Chemical products plant and machine operators	0.792	1	1
8332	Heavy truck and lorry drivers	0.793	1	1
8121	Metal processing plant operators	0.800	1	1
8122	Metal finishing, plating and coating machine operators	0.800	1	1
4321	Stock clerks	0.828	1	1
4412	Mail carriers and sorting clerks	0.862	1	1
3324	Trade brokers	0.867	1	1
4322	Production clerks	0.875	1	1
4312	Statistical, finance and insurance clerks	0.897	1	1
5230	Cashiers and ticket clerks	0.897	1	1
3321	Insurance representatives	0.900	1	1
4222	Contact centre information clerks	0.900	1	1
4323	Transport clerks	0.926	1	1
4311	Accounting and bookkeeping clerks	0.933	1	1

The *mean*, *mode* and *consensus* (at least 75% responded with yes or no) were calculated for each profession

occupations being fully substituted by technologies. The way we ask our experts to label the individual professions allows comparability to Frey and Osborne (2017) who ask: *"Can the tasks of this job be sufficiently specified, conditional on the availability of big data to be performed by state of the art computer-controlled equipment"*.

Experts were allowed to avoid answering the question in relation to as many jobs as they wished. However, in the end, only a small minority of jobs remained unlabelled. In order to extract an indicator of future digitization that is unique to each profession, we calculated three measures: the *mean* and *mode* of all expert opinions, as well as an indicator of the experts' *consensus* on each profession. The *consensus* is equivalent to the mode, but only for those professions to which at least 75% of all experts attributed the same label. With this definition of *consensus*, 45 professions remained and received a binary label, as shown in Table 1.

Our expert opinions should be better suited for Austria than the opinions stemming from the Oxford seminar. Machine learning experts all over the world should be familiar with the scientific principles of the technologies disrupting the labour market, but they may not be fully aware of the social environments in which smart technologies could be implemented. For example, even when chatbots in the financial service sector become market-ready from a technological point of view, some customers will still prefer human interaction. Not surprisingly, our academic experts are slightly more optimistic about algorithms being able to substitute tasks in Austria than our industry experts who have to account for the customer side as well as the political circumstances.[4] The gap between technological readiness and implementation might very well vary to a sizeable extent between countries and cultural backgrounds.

Following the method by Arntz et al. (2016), we match the profession codes from our survey to the profession groups from the Austrian and German samples of the 2015 OECD survey of the PIAAC. The PIAAC survey supplies our analysis with individual characteristics, as well as job- and firm-level indicators. In addition, the survey contains information about the frequency of specific tasks performed by interviewed individuals during their average working routine. These tasks include human interaction, IT usage, physical work, problem-solving, reading or understanding, and writing or calculating. As the individuals provided answers about the frequency by which they undertake a given task, we normalized the answers according to the value of the working hours as follows: *'on a daily basis'* (value=1), *'less than daily, but more than once a week'* (value=1/2), *'less than once a week, but more than once a month'* (value=1/7), *'less than once a month'* (value=1/30), or *'never'* (value=0). This labelling is likewise applied by Arntz et al. (2016), since it reflects the differences in scale between days, weeks and months.

Finally, our expert opinions about the future change of professions are matched to the PIAAC data in order to estimate inferential models about the automation susceptibility of jobs. The opinions about professions are matched via the ISCO-08 classification for each individual's job. As only the German PIAAC sample contains the respective ISCO-08 Level 4 job classifications, we will fit the inferential models only with the labelled subset of German employees and will then translate the results back to Austrian data.[5] We test two types of inferential models whereby the *consensus* indicator serves as the dependent variable in the binary model and the *mean* indicator in the fractional model. Personal-, job- and firm-level controls, as well as task frequencies, are included in the models (see descriptive details in Table 2).[6] All measures are considered at the individual level. The final sample contains 4438 individuals: 2387 from Germany, who we use to fit our inferential models at the ISCO-08 Level 4 job classification, and 2051 from Austria, for whom we want to predict their exposure to digitization.

[4] Figure 8 in the Appendix provides comparisons of academic and industry experts' judgements about digitization susceptibilities of jobs.

[5] The skill and task distributions in the German and Austrian PIAAC data are very similar so that we fear no major distortions. A comparison can be found in Fig. 7 in the Appendix.

[6] The correlation analysis in Table 5 in the Appendix across all characteristics only indicates a sizeable association between the three test score variables.

4 Results

As we aim at predicting digitization probabilities, we need to find a model that provides a sufficiently good fit. For this purpose, we apply models that are similar to the ones tested by Frey and Osborne (2017): First, we apply a logit model as illustrated in column (1) in Table 3. Second, we test a linear discriminant analysis (LDA) with a Bayesian estimation of the dependent variable (James et al. 2013, Chapter 4).[7] In order to compare the logit and LDA models, we look at the respective out-of-sample correlations. The comparison shows that both models perform very similarly with correlations of slightly above 0.6. Accordingly, the predictions of both models are very similar as summarized in Table 4. We favor the simpler logit model as it performs well and provides us with interpretable beta coefficients (the LDA does not and is therefore not included in Table 3).

We deploy the logit model (1) to predict the digitization probabilities. We proceed according to the following formula:

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta' X)}}, \quad \beta' X = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k \tag{1}$$

The digitization probabilities P(y=1|X) are estimated for all individuals in the sample, based on their set of characteristics ($\beta' X$) including individual-, job- and firm-specific characteristics as well as their task structure. In doing so, individuals with professions that have not been judged by our experts now also obtain a probability. The average estimated probabilities of future digitization are shown in Fig. 1. We find the usual bimodal distribution with many jobs being exposed to digitization and many that are not. The distribution mirrors the initial expert *consensus*.

Based on the *consensus* of our experts, we are able to specify a degree of future digitization for 45 occupations. More than 75% of our experts agreed that the characteristic tasks of these professions will (or will not) change to a significant degree with the development of digital technologies and mobile robotics. With the use of the PIAAC data set, we are able to relate the degree of digitization to personal characteristics and occupation-specific tasks. Based on these relationships, we can predict the degree of digitization for all professions in the data set. In contrast to the work by Frey and Osborne (2017), we apply local experts' opinions and perform our estimations on the basis of individual characteristics.

For some tasks we see a clear relationship with the *consensus* of our experts. In Fig. 2, the frequencies of the 40 tasks are compared to the *consensus* of our experts. On average, some tasks, such as coding, are, on average, performed less than once a month, while others, such as sharing information with others, are carried out on an almost daily basis. For some activities, prevalence does not differ significantly between the two *consensus* job groups. However, for most of the activities, a clear separation between the *consensus* groups is visible. Activity involving long physical

[7] The probability of belonging to class k, given characteristics X, is described by $P(Y = k|X = x) = \frac{f_k(x)\pi_k}{P(X=x)}$, while $f_k(x)$ describes the probability of $X = x$, given that $Y = k$, while π_k is the prior probability of observing $Y = k$.

Table 2 Summary of characteristics

Name	Observations	(in %)				
Age group						
< 16–19	104	(5.1)				
20–24	195	(9.5)				
25–29	255	(12.4)				
30–34	255	(12.4)				
35–39	273	(13.3)				
40–44	309	(15.1)				
45–49	267	(13.0)				
50–54	242	(11.8)				
55–59	119	(5.8)				
> 60	32	(1.6)				
Gender						
Male	1002	(48.9)				
Female	1049	(51.1)				
Firm—sector						
Public or NGO	668	(32.6)				
Private	1383	(67.4)				
Firm—size						
1–10	458	(22.3)				
11–50	607	(29.6)				
51–250	480	(23.4)				
251–1000	326	(15.9)				
> 1000	180	(8.8)				
Job—responsibility						
Yes	1182	(57.6)				
No	869	(42.4)				
Job—experience						
< 1 month	585	(28.5)				
1 to 6 months	282	(13.7)				
7 to 11 months	157	(7.7)				
1 or 2 years	472	(23.0)				
3 years or more	555	(27.1)				
Job—education						
< ISCED 3	252	(12.3)				
ISCED 3–4	1169	(57.0)				
ISCED 5+	630	(30.7)				
Skills—PC						
low	690	(33.6)				
moderate	1211	(59.0)				
complex	150	(7.3)				
Education		Min.	25%	Mean	75%	Max.
Years in full-time education		4.0	13.0	14.3	16.0	20.0

Table 2 (continued)

Name	Observations	(in %)				
Skills[a]						
Problem-solving		168.1	268.1	290.1	313.6	404.3
Numeracy		160.4	269.6	294.8	321.7	409.7
Literacy		156.8	263.6	285.8	310.5	396.2

[a]Skills are assessed via the survey of adults skills in the PIAAC on a scale between 0 and 500

work is less commonly performed in professions that are expected to change during digitization, according to our experts. Other activities show the exact opposite pattern. Calculating or the use of computer software *Excel*, for example, is much more prevalent in professions that are expected to change. This observation, confirmed by the findings of the inferential model, is a first indication that professions with a high degree of computer-based office routines are more likely to change in light of digital technologies.

In addition to the 40 tasks, individual-, job- and firm-specific characteristics can help explain the consensus opinions of our experts, as shown in Table 3. The logit model (1) indicates that—apart from work activities—variables such as education, firm sector, firm size, job responsibility and job education are related to the degree of future digitization. Individuals who work in the public sector, in smaller firms or in jobs that require education or experience, are typically less likely to be employed in an occupation that is going to change significantly.

Among occupations, there is a clear trend (Figs. 3, 4): Clerical support workers, who perform simple computer-based office routines, are highly susceptible to technological changes. This is in line with previous findings (Frey and Osborne 2017; Nagl et al. 2017). On the other hand, professionals, who work with complex and unstructured information, and skilled workers in agricultural fields, who perform physical work, are less likely to experience major changes in their job profile. Professional occupations involving teaching and healthcare within legal, social or cultural environments (Fig. 4) exhibit particularly low probabilities of digital transformation. This finding is consistent for individuals working in a job that requires an academic degree. On average, most occupations show a probability of change between 40 and 60%.

Up to this point, we have worked with a binary model which is similar to Frey and Osborne (2017) who also start with binary opinions of experts and extrapolate them via a classification model for all occupations. Bowles (2014) directly transfers these estimations to European labour markets. Both studies conclude that a high share of workers (47% in the US and 54% in Austria) are at high risk of computerization. Our estimate for Austria using the logit model is 45% (see Table 4). Arntz et al. (2016) and Nagl et al. (2017), on the other hand, begin with discrete probabilities and apply a fractional model in order to extrapolate. In comparison, they show that only about 12% and 9%, respectively, have a digitization risk of more than 70%.

Table 3 Model (1) works with a binary outcome of job digitalisation, while the outcome of model (2) is continuously measured between 0 and 1

	Dependent variable	
	Binary (1)	Fractional (2)
Age 19 or younger	–	–
Age 20–24	0.32	− 0.002
	(0.64)	(0.34)
Age 25–29	0.80	0.04
	(0.72)	(0.36)
Age 30–34	1.84**	0.19
	(0.72)	(0.36)
Age 35–39	1.17	0.12
	(0.74)	(0.36)
Age 40–44	2.11***	0.36
	(0.73)	(0.35)
Age 45–49	1.26*	0.16
	(0.70)	(0.36)
Age 50–54	1.85**	0.25
	(0.78)	(0.36)
Age 55–59	0.60	0.27
	(0.81)	(0.39)
Age 60 or older	− 0.56	0.07
	(1.02)	(0.46)
Gender female	–	–
Gender male	0.10	− 0.003
	(0.30)	(0.13)
Education (years)	0.51	0.06
	(0.43)	(0.17)
Education (years)^2	−0.03*	− 0.004
	(0.02)	(0.01)
Firm sector (private)	–	–
Firm sector (public/NGO)	− 1.90***	− 0.50***
	(0.35)	(0.14)
Firm size 1–10	–	–
Firm size 11–50	0.60	0.18
	(0.42)	(0.16)
Firm size 51–250	0.82**	0.37**
	(0.42)	(0.18)
Firm size 251–1000	0.80	0.37*
	(0.49)	(0.19)
Firm size > 1000	1.79***	0.41*
	(0.57)	(0.21)
Job responsibility (no)	–	–

Table 3 (continued)

	Dependent variable	
	Binary (1)	Fractional (2)
Job responsibility (yes)	0.95***	0.11
	(0.35)	(0.14)
Job experience < 1 month	–	–
Job experience 1–6 months	− 0.31	− 0.03
	(0.44)	(0.18)
Job experience 7–11 months	− 0.99**	− 0.07
	(0.49)	(0.19)
Job experience 1–2 years	− 0.47	− 0.02
	(0.42)	(0.17)
Job experience 3 years or more	− 0.75*	− 0.16
	(0.45)	(0.19)
Job education < ISCED 3	–	–
Job education ISCED 3–4	− 0.20	− 0.20
	(0.45)	(0.20)
Job education ISCED 5+	− 2.54***	− 0.81***
	(0.59)	(0.25)
PC skills: low	–	–
PC skills: moderate	0.46	0.14
	(0.36)	(0.15)
PC skills: complex	− 1.34*	− 0.23
	(0.81)	(0.31)
Skills problem-solving	− 0.01*	− 0.0000
	(0.01)	(0.003)
Skills numeracy	0.02*	0.005
	(0.01)	(0.004)
Skills literacy	− 0.01	− 0.005
	(0.01)	(0.004)
Tasks		
Cooperating or collaborating with co-workers	− 0.40	− 0.10
	(0.42)	(0.17)
Sharing work-related information with co-workers	0.46	0.04
	(0.44)	(0.20)
Instructing, training or teaching people, individually or in groups	− 0.03	− 0.08
	(0.49)	(0.20)
Making speeches or giving presentations in front of five or more people	− 1.50**	− 0.29
	(0.73)	(0.28)
Selling a product or selling a service	0.47	0.10
	(0.38)	(0.16)
Advising people	− 0.35	− 0.07
	(0.38)	(0.16)

Table 3 (continued)

	Dependent variable	
	Binary (1)	Fractional (2)
Persuading or influencing people	− 0.70*	− 0.23
	(0.40)	(0.16)
Negotiating with people either inside or outside one's firm or organization	0.66	0.09
	(0.43)	(0.17)
Using email	0.57	0.18
	(0.53)	(0.21)
Using the Internet in order to better understand issues related to one's work	0.78*	0.06
	(0.44)	(0.18)
Conducting transactions over the Internet, e.g., buying or selling	0.21	0.15
	(0.50)	(0.20)
Using spreadsheet software, for example, Excel	0.28	0.14
	(0.41)	(0.18)
Using a word-processing package, for example, Word	− 0.60	− 0.06
	(0.45)	(0.18)
Using a programming language to program or write computer code	0.61	0.11
	(0.82)	(0.34)
Participating in real-time discussions over the Internet, e.g., online conferences	2.27*	− 0.14
	(1.34)	(0.39)
Working physically for a long period	− 2.21***	− 0.49***
	(0.40)	(0.16)
Using skill or accuracy with hands or fingers	0.13	− 0.03
	(0.35)	(0.14)
Planning one's own activities	− 0.73**	− 0.17
	(0.37)	(0.14)
Planning the activities of others	− 0.02	− 0.06
	(0.49)	(0.21)
Organizing one's own time	0.08	0.04
	(0.39)	(0.16)
Solving simple problems, which require no more than 5 min of attention	− 0.10	− 0.03
	(0.38)	(0.16)
Solving complex problems, which require at least 30 min of attention	− 0.88*	− 0.11
	(0.51)	(0.21)
Reading directions or instructions	0.46	0.08
	(0.38)	(0.15)
Reading letters, memos or emails	0.53	0.12
	(0.59)	(0.24)
Reading articles in newspapers, magazines or newsletters	0.51	0.02
	(0.45)	(0.17)
Reading articles in professional journals or scholarly publications	0.06	− 0.05
	(0.65)	(0.24)

Table 3 (continued)

	Dependent variable	
	Binary (1)	Fractional (2)
Reading books	− 2.70***	− 0.33
	(0.77)	(0.27)
Reading manuals or reference materials	− 0.01	0.03
	(0.49)	(0.20)
Reading bills, invoices, bank statements or other financial statements	1.10***	0.22
	(0.41)	(0.17)
Reading diagrams, maps or schematics	0.46	0.05
	(0.39)	(0.16)
Writing letters, memos or emails	− 0.55	− 0.02
	(0.55)	(0.22)
Writing articles for newspapers, magazines or newsletters	3.09**	0.08
	(1.53)	(0.62)
Writing reports	− 1.87***	− 0.44***
	(0.39)	(0.16)
Filling in forms	− 0.08	0.10
	(0.35)	(0.15)
Calculating prices, costs or budgets	− 0.71	− 0.09
	(0.45)	(0.17)
Using or calculating fractions, decimals or percentages	0.34	0.07
	(0.42)	(0.18)
Using a calculator (either hand-held or computer-based)	1.49***	0.41**
	(0.38)	(0.17)
Preparing charts, graphs or tables	0.05	− 0.03
	(0.60)	(0.22)
Using simple algebra or formulas	0.40	0.11
	(0.45)	(0.18)
Using more advanced mathematics or statistics	− 0.06	− 0.20
	(1.11)	(0.37)
Constant	− 0.50	− 0.10
	(3.15)	(1.26)
Observations	868	1658
Akaike Inf. crit	590.68	1860.93

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

To compare our results to the work by Arntz et al. (2016) we further apply a fractional response model (see column (2) in Table 3), which provides an out-of-sample correlation of even 0.68.[8] In this model, the mean of the experts' opinions is

[8] $E(y|X) = \frac{e^{(\beta' X)}}{1+e^{(\beta' X)}}$, while $\beta' X = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$. See also Papke and Wooldridge (1996).

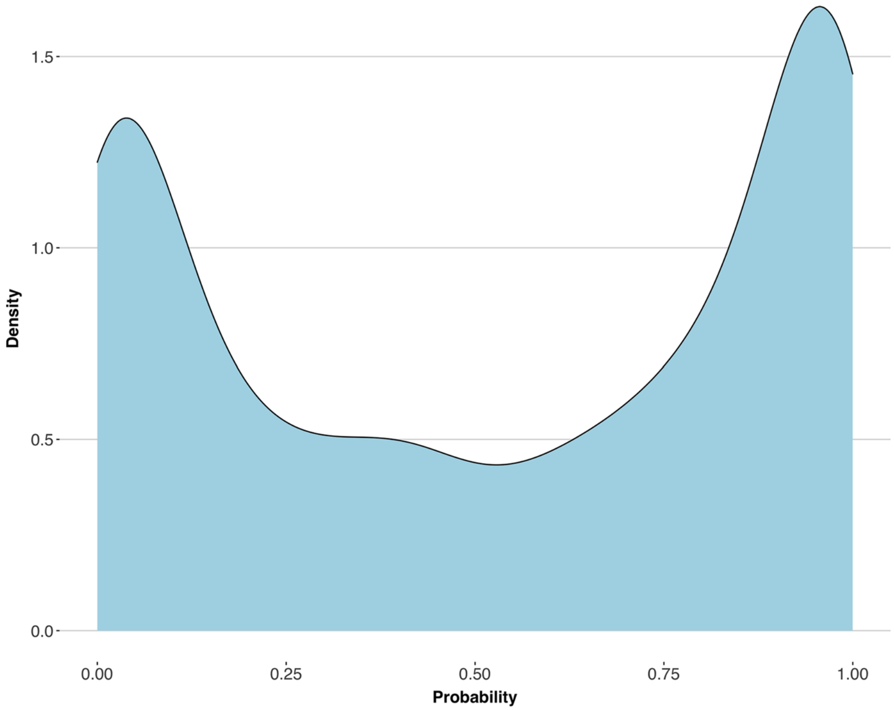

Fig. 1 *Future digitalization*: Jobs in Austria are polarized between high and low levels of future digitalization. The distribution of individual levels of future digitalization mirrors the initial estimation of our experts

considered as the dependent variable. Accordingly, the fractional model refers to a larger sample size.

When comparing our findings, clear differences emerge with regard to the degree of susceptibility to digital technologies. Our estimate of the share of workers at high risk of computerization reduces from 45% using a logit approach to 12% using a fractional model and is therefore much lower than in Frey and Osborne (2017). Heterogeneity, as pointed out by Arntz et al. (2017, 2020), does also play a role. Would we not estimate our fractional model using individual but median task structures by occupation (hence, assuming that all workers within the same occupation perform the same tasks), we would predict 20% of jobs to be at risk. This observation is in line with previous findings by Arntz et al. (2017). Smaller predicted probabilities will come out when heterogeneity is taken into account and non-binary models are used.

Hence, our model testing confirms that the contradicting findings in the literature are driven by (a) variation in tasks at the job level versus the occupational level (while Frey and Osborne 2017 analyze tasks on the occupation level and thus allow for variation in tasks *between* occupations, Arntz et al. (2016) take a step further to the job level allowing for variations of tasks *within* the same occupation) but also by

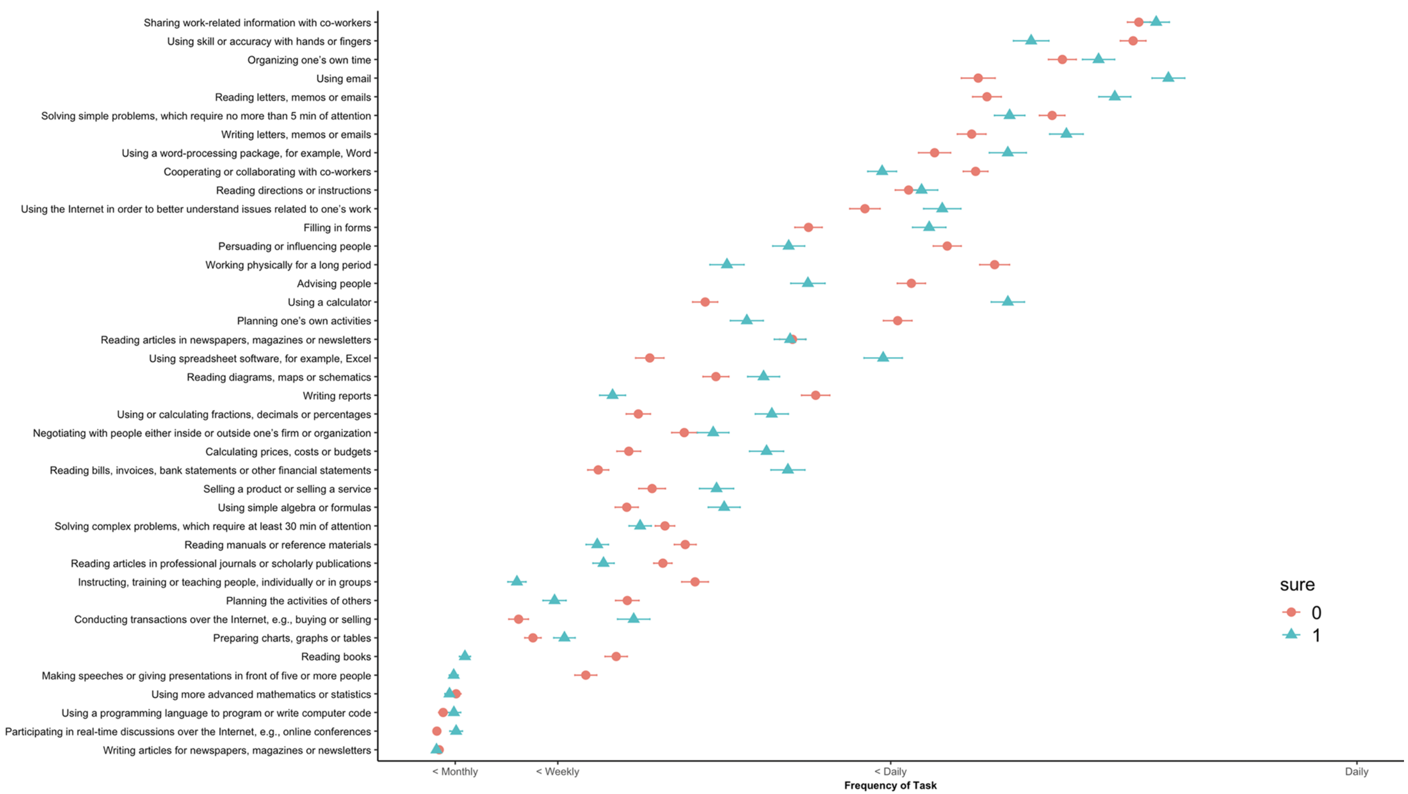

Fig. 2 *Tasks at work*: Of the 40 tasks, some are performed on a daily basis, while others are carried out only once a month. Some of the activities vary significantly between jobs with a high and low degree of future digitalization

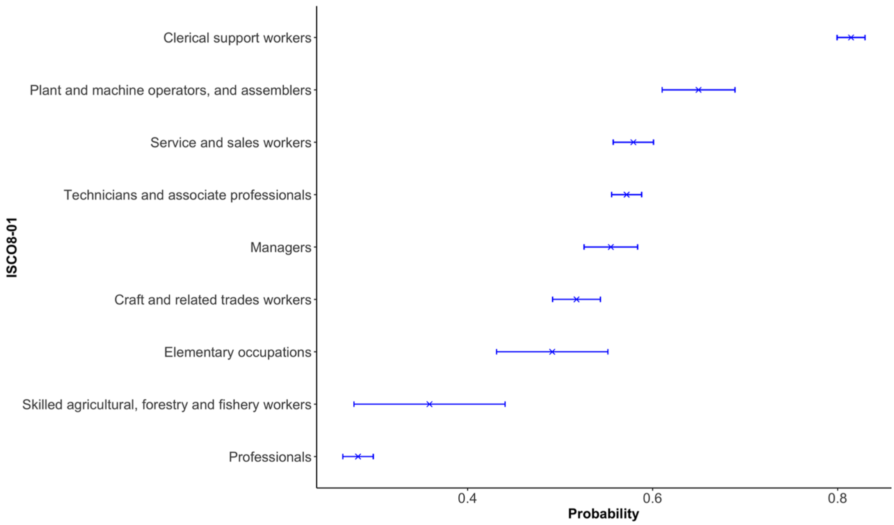

Fig. 3 *ISCO Level 1*: For the top level of occupations, clerical professions have, by far, the highest risk of future digitalization. Professionals are at the lower end of the scale

(b) the choice of the model. Binary models yield a bimodal distribution of predicted probabilities with large high-risk groups. Fractional models lead to a bell-shaped distribution of probabilities with relatively low levels of high-risk individuals. Our own estimations for a fractional model (Fig. 5) confirm this conjecture. The ranking of occupational classes does not change significantly after the fractional model (Fig. 6) has been used. However, predicted probabilities converge towards the mean.

Similarly, when moving the threshold of the *consensus* indicator from our chosen value of 75–50%, the predictions of the binary models approach the ones of the fractional model. The predicted digitization risks (see lower part of Table 4) are now somewhat in between the initial logit result and the fractional result. In turn, if we increase the *consensus* threshold to 90%, the predicted risks increase even further. Hence, the more we force expert opinions into a yes/no-setting (by reducing the consensus threshold), the lower are the shares of jobs at risk as there is more underlying uncertainty in our expert opinions and, hence, our inferential models produce less clear-cut results. On the other hand, if we use the 90% consensus, only those jobs are used that are clearly at risk (resp. not at risk); the prediction will reflect that in terms of a bimodal distribution.

Model choice also entails issues of sample selection and sample size: When comparing the estimation outcomes of the binary and fractional model (Table 3), the results of the latter contain a lower number of covariates, which are statistically relevant for the degree of digitization. The fractional model hardly shows any statistical significance concerning the covariates that have not been relevant in the binary model. In the fractional model, job experience, for example, shows no statistical significance. Likewise, tasks like speaking in front of humans or reading books are not significant in the case of the fractional model environment. This general observation is not surprising from a statistical point of view, since the formally strict binary

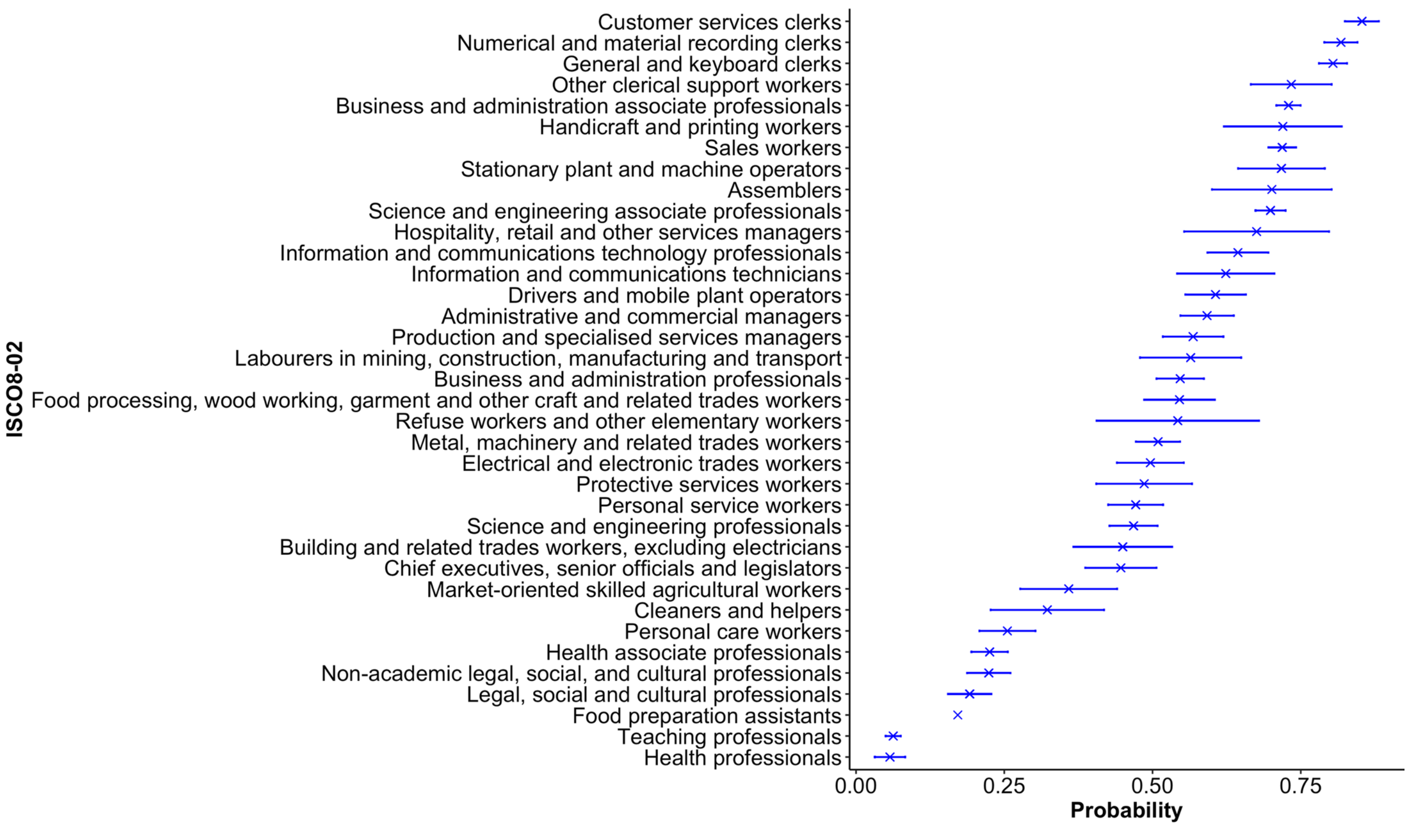

Fig. 4 *ISCO Level 2*: Professional occupations involving teaching and healthcare, within legal, social or cultural environments, exhibit particularly low probabilities of digital transformation

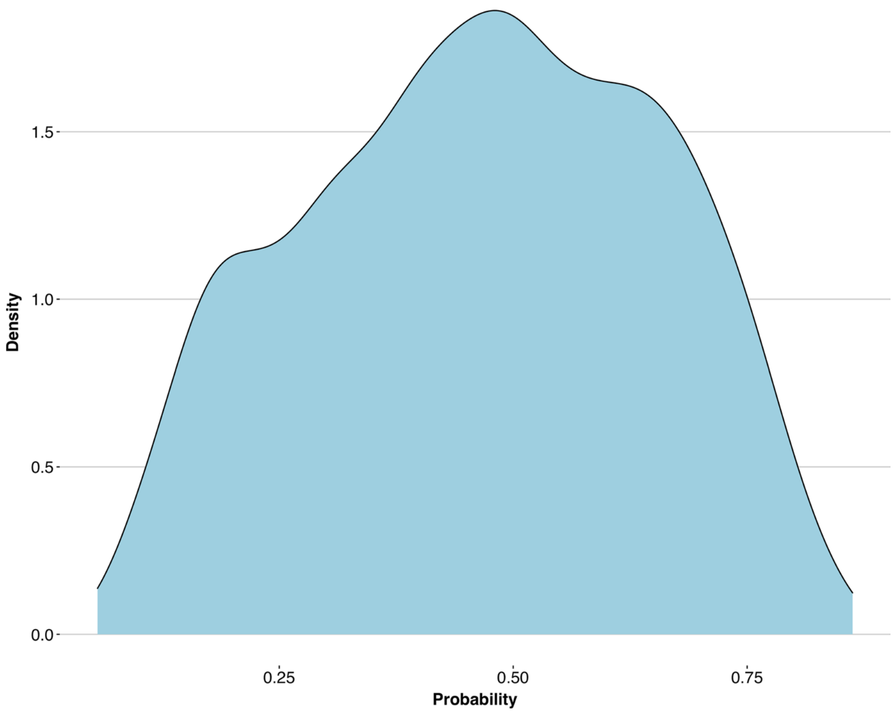

Fig. 5 *Fractional model*: Similar to the work by Arntz et al. (2016) and Nagl et al. (2017), the application of a fractional model (Papke and Wooldridge 1996) yields a bell-shaped distribution of predicted probabilities

outcome in a small sample has now been changed to a smooth continuous scale in a sample twice the original size. However, it becomes clear that some covariates, such as physical work, writing reports, performing calculations or firm characteristics, are still aligned with the distribution of the fractional model. The distribution of other covariates has been polarized by the truncation of the binary model. Given that the fractional model performs better than our binary model in terms of out-of-sample correlations, would imply that lower shares of jobs at risk are more plausible than higher ones.

5 Conclusion

Our model explicitly diverges from the approach taken in previous contributions in this field. We assume that the diversity of previous estimations of job susceptibility not only stems from (a) task-variation at the job level but also from (b) model specification. In order to test this assumption we conducted a case study with local expert opinions about near-term changes in occupations in Austria. This is a significant conceptual improvement in contrast to prior investigations such as Arntz et al.

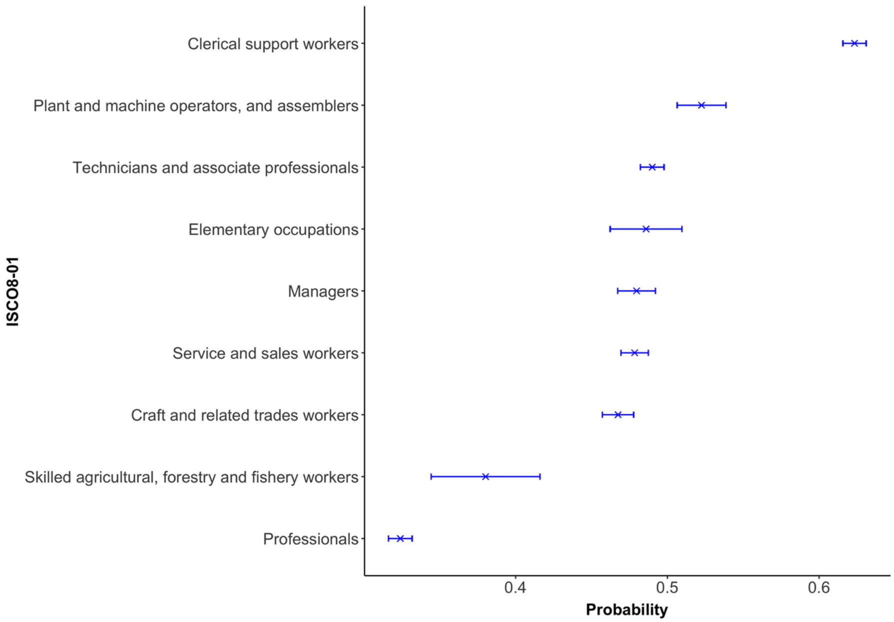

Fig. 6 *ISCO Level 1*: The ranking of occupational classes does not change for the fractional model. However, predicted probabilities converge to the mean

(2016) or Bowles (2014) who rely on the judgement of machine learning experts concerning the US labour market (stemming from the workshop organized by Frey and Osborne (2017)). Past findings are, in part, contradictory. 47% of jobs in the US (54% in Austria) share a high risk of digitization, according to Frey and Osborne (2017) and Bowles (2014), while Arntz et al. (2016) and Nagl et al. (2017) estimate this share to be 12% and 9%, respectively, for Austria.

Our findings show that in fact heterogeneity among tasks performed within an occupation reduces the risk of automation—as pointed out by earlier research (Arntz et al. 2016, 2017, 2020; Nedelkoska and Quintini 2018). However, also model selection plays a major role in explaining the different digitization shares. Given these results, the potential job displacement risks from digitization need to be interpreted with caution. Recent research claims that the findings by Frey and Osborne (2017) are exaggerated as they ignore differences in tasks among jobs within the same occupation. Hence, this research finds lower shares at high risk. Lower probabilities seem to be more plausible as task heterogeneity within occupations lowers the risk as well as allowing for more uncertainty in expert opinions using a less strict consensus or a fractional model; the latter provides the best model fit. Also, our results indicate high sensitivity of binary models to the subjective choice of the threshold consensus.

To avoid misinterpretation in the public debate, one should be aware that the estimates are driven by expert opinions on the feasibility of computers to perform human tasks. This does not mean that these tasks will be immediately replaced by machines. These estimates do not tell us anything about cost efficiency (Acemoglu

Table 4 When comparing the outcome reported in past contributions with our findings, the choice of model clearly dictates the resulting probabilities

Author	Initial input	Model type	Level of variation	Consensus threshold (%)	High risk (%)	Country
Frey and Osborne (2017)	Binary (0/1)	Classification	Occupation	75	47	US
Bowles (2014)	*transfer of* Frey and Osborne (2017)		Occupation	–	54	AT
Arntz et al. (2016)	Discrete (0–1)	Fractional	Job	–	12	AT
Nagl et al. (2017)	Discrete (0–1)	Fractional	Job	–	9	AT
Own calculations	Discrete (0–1)	Fractional	Job	–	12	AT
Own calculations	Binary (0/1)	Logit	Job	75	45	AT
Own calculations	Binary (0/1)	LDA	Job	75	48	AT
Own calculations	Binary (0/1)	LDA	Job	50	25	AT
Own calculations	Binary (0/1)	LDA	Job	90	54	AT
Own calculations	Binary (0/1)	Logit	Job	50	24	AT
Own calculations	Binary (0/1)	Logit	Job	90	57	AT
Own calculations	Discrete (0–1)	Fractional	Occupation	–	20	AT

Models with a binary dependent variable lead to bimodal distributions with large high-risk groups. Fractional models yield bell-shaped distributions with small high-risk shares. Binary models would only yield less drastic outcomes when the respective consensus threshold is small. Taking heterogeneity into account also contributes to smaller risk shares and Restrepo 2018; Brynjolfsson et al. 2019), social acceptance (Pratt 2015) and the legal difficulties (e. g. liability concerns) (Bonnefon et al. 2016; Thierer and Hagemann 2015) when it comes to replacing workers by machines. Further, these estimates focus solely on the replacement side of technological advancement. They do not entail the possibility of job creation nor of job adaptation (Acemoglu 1998). Hence, these estimates, regardless of model selection, display, at best, an upper bound of labor market effects.

Nevertheless, our findings show that the tasks that humans perform during their typical working day are of significant importance when determining the impact of digital technologies on the future workspace. Activities such as writing reports reduce the impact of technologies. On the other hand, tasks such as calculations will lead to a stronger change in job profiles in the next decade. Furthermore, as the current generation of technological progress has a stronger impact on cognitive and routine tasks than on physical labour, the extent of physical work within a job profile reduces the effect of digital change. Although the future of work will most likely be a complementary partnership between humans and computers, workers performing computer-related routine activities, such as spreadsheet calculations or Internet usage (Stephany 2020, 2021; Stephany et al. 2021), are under stronger pressure to adapt.

Our results indicate that some jobs can expect to change more than others during the current phase of digital progress. This is surely not the first time in history that this has happened. During the industrial revolution, technological advancements made manufacturing jobs less intensive in terms of monotonous physical labour. In contrast to the age of the steam engine, today's technologies, such as algorithms, unfold their potential in disciplines that require routine cognitive effort. Typical computer-backed office tasks, such as in the clerical professions, are more exposed to digital transformation than occupations marked by physical labour. Likewise, jobs in which complex information is processed and that require a high level of education and training are less prone to digital change in the near future. Teaching and healthcare professionals working within legal, social or cultural environments belong to occupations with the lowest level of technological pressure. In the near future, these disciplines can be regarded as a sustainable choice for future generations seeking job security in unsteady times.

In addition, while most research focuses on human labour that can be replaced by technology, little attention has been given to the effect that digital technologies have on job creation. As our findings improve the understanding of the displacement effect of technologies, more research should be conducted in order to incorporate the effect of job creation, and in turn appreciate the full impact of the technological change on the labour market.

Appendix

See Table 5, Figs.7 and 8.

Table 5 The correlation matrix shows that there are no pronounced correlations across variables, except in the case of the test scores for numeracy and literacy

	Age group	Gender	Education	Education^2	Firm—sector	Firm—size	Skills—PC	Skills—prob-solv.	Skills—numeracy	Skills—literacy	Job—respons.	Job—education	Job—experience
Age group	1.000												
Gender	− 0.031	1.000											
Education	0.120	0.001	1.000										
Education^2	0.108	− 0.001	0.992	1.000									
Firm—sector	− 0.153	− 0.134	− 0.177	− 0.186	1.000								
Firm—size	0.014	− 0.169	0.101	0.104	− 0.082	1.000							
Skills—PC	− 0.015	− 0.122	0.223	0.223	0.072	0.090	1.000						
Skills—prob-solv	− 0.298	− 0.122	0.316	0.312	0.088	0.158	0.305	1.000					
Skills—numeracy	0.018	− 0.184	0.418	0.414	0.019	0.116	0.288	0.744	1.000				
Skills—literacy	− 0.110	− 0.051	0.424	0.421	− 0.025	0.123	0.279	0.810	0.865	1.000			
Job—respons	0.167	− 0.220	0.138	0.135	0.021	0.071	0.066	0.024	0.097	0.058	1.000		
Job—education	0.243	− 0.013	0.581	0.576	− 0.198	0.113	0.269	0.209	0.358	0.338	0.161	1.000	
Job—experience	0.244	− 0.196	0.197	0.194	0.126	0.109	0.179	0.064	0.141	0.105	0.302	0.300	1.000

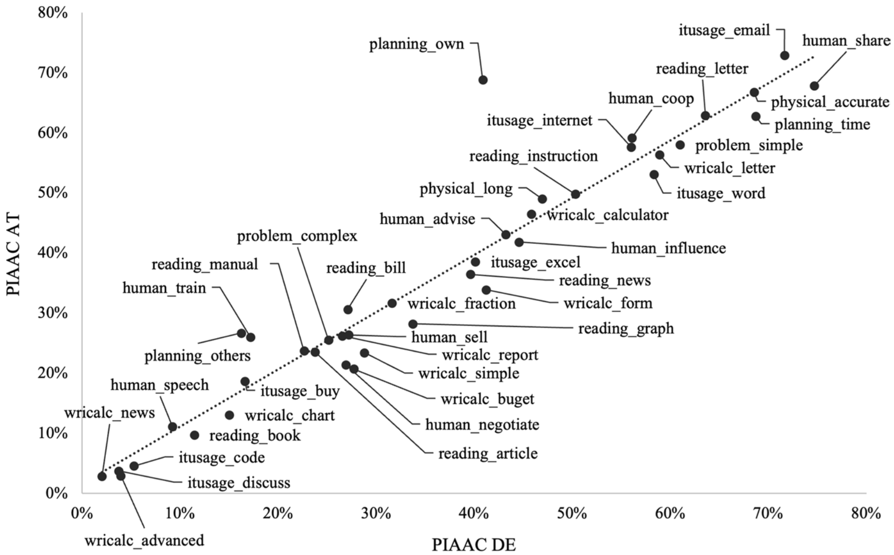

Fig. 7 Comparison of task distributions in the German and Austrian PIAAC data. Mean task frequencies in both countries are mostly located along the 45° line; hence, they are pretty similar

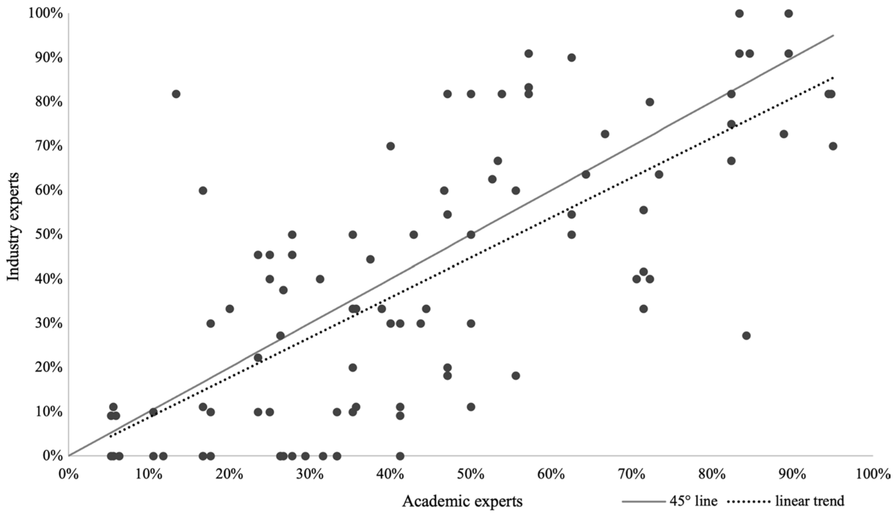

Fig. 8 Comparison of academic and industry experts with regard to digitization susceptibilities of jobs. Academic experts have a slightly stronger believe that jobs can be digitized (as the trend line is flatter than the 45° line on which both groups of experts would have the same opinion)

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