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# Impacts of Industry 4.0 on industrial employment in Germany: A comparison of industrial workers' expectations and experiences from two surveys in 2014 and 2020

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## ABSTRACT

Companies across the globe have intensified the digital interconnectedness of their manufacturing processes. Much attention was devoted to how industrial employment will be affected in this new production paradigm. In this paper, we use survey data collected from German industrial workers in 2014 and 2020 to contribute to the literature on digitalisation and industrial employment. This is the first scientific study on Industry 4.0 that empirically deals with the development of key parameters of industrial employment over time. Our findings support the argument that whilst increased digital interconnectedness creates more opportunities for highly skilled workers, the extent to which manual workers will be substituted is often overestimated. Second, our data suggests that the operations of larger companies tend to be more highly digitally interconnected than those of smaller firms. We also provide evidence that German industrial workers are less likely to expect substantial job losses through digitalisation than in 2014.

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## KEYWORDS

Digital interconnectedness; industry 4.0; industrial employment; qualifications; future of work

## 1. Introduction

In the last decade, companies across the globe have intensified the digital interconnectedness of their industrial manufacturing processes (Benitez et al., 2020; Kamble et al., 2018; Yadav et al., 2020; Zhou et al., 2020). By integrating technologies and processes such as automation, simulation, smart robotics, and autonomous decision-making systems, industrial producers aim to enhance the flexibility and efficiency of their operations by enabling the self-organisation and self-optimisation of manufacturing processes (Bai et al., 2020; Beier et al., 2020; Frank et al., 2019; Rajput & Singh, 2020; Sony, 2020). As with any major transformation in manufacturing, much attention is devoted to how industrial employment will be affected in this new production paradigm. In this regard, although digital interconnectedness is often linked to the substitution of workers and rising unemployment (Bal & Erkan, 2019; Frey & Osborne, 2017; OECD, 2019; World Bank, 2020), numerous scholars contend that the extent to which digital interconnectedness will decrease employment is

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often overestimated (Arntz et al., 2016; Dengler & Matthes, 2018; Krzywdzinski, 2017; D. Spencer & Slater, 2020). In some cases, it is even argued that digital interconnectedness will create more jobs in the industrial sector than it will destroy (Evangelista et al., 2014; Su et al., 2022; World Economic Forum, 2018).

However, empirical evidence on the effects of digital interconnectedness on key parameters of industrial employment (such as staffing and changing qualifications) are scarce and no scientific study has so far dealt with the development of these parameters over time. In this paper, we therefore aim to better understand how industrial interconnectedness impacts industrial employment by analysing two surveys which were conducted amongst employees working in German industrial production companies in 2014 (Beier et al., 2017) and 2020.

Accordingly, we pose the following research questions (RQ):

- RQ1: What changes in industrial employment are expected from digital interconnectedness with regard to staffing and required qualifications?
- RQ2: What influence do the variables company size and sector (development, manufacturing, assembly) have on these changes?
- RQ3: How do these expectations change over time?

We make three contributions to the literature. First, we add to the debate on the transformation of industrial employment by analysing how our respondents expect increased digital interconnectedness to impact staffing and required qualifications in their respective companies. Next, we analyse how these expectations are impacted by the size of the firm which the respective study participants work for. Finally, we compare the findings from our two analyses (2014 and 2020 surveys) to better understand how expectations and predictions amongst employees have changed as digital interconnectedness of industrial production has become more widespread in Germany. Throughout the paper, we use the term ‘digital interconnectedness’ to avoid confusion caused by misinterpretations of the concepts *Industry 4.0* and *Industrial Internet of Things* (IIoT). This reflects the view that whether one uses the decidedly German term *Industry 4.0* (Beier et al., 2021; Pfeiffer, 2016), or the more general *Industrial Internet of Things* (IIoT), the core of the concept remains the digital interconnection of manufacturing systems and processes through information and communication technologies.

## 2. Theoretical background

### 2.1. Digital interconnectedness & industrial employment

Although most scholars agree that digital interconnectedness will make certain manual tasks redundant, there is little empirical evidence for the claim that this will result in mass technological unemployment (Abramova & Grishchenko, 2020; Fu et al., 2021; Stettes et al., 2017). Next to these empirical gaps, research suggests that – rather than passively waiting to see whether their jobs will be substituted or not – workers have agency and can adapt to new challenges (Arntz et al., 2016), resist changes in the workplace (Hirsch-Kreinsen, 2016), and actively shape the way in which new machines and work processes are incorporated into their jobs (Bauer et al., 2018; Benešová &

Tupa, 2017; Hammershøj, 2019; Helming et al., 2019). Next to human agency, the impact of digital interconnectedness is strongly dependent on contextual factors such as countries' social protection mechanisms, education policies, the structure of the workforce (Arntz et al., 2016; Grigoli et al., 2020; Hirsch-Kreinsen, 2017; OECD, 2019; E. Weber, 2017), as well as company-level elements such as workplace organisation, management strategies, and the politicisation of the labour force (Krzywdzinski, 2017; Valenduc & Vendramin, 2017).

Other barriers to an increasing automation of labour are low wages and permissive employment regulation (D. Spencer & Slater, 2020). On a similar notion, sticking to labour-intensive processes might in some cases simply be less cost-intensive and high investments into automation technology might also contradict with shareholder desires for short-term profits, while high wages can work as an incentive to automate (Lewis & Bell, 2019; Upchurch, 2018). Especially in highly industrialized countries, the limited availability of qualified workforce as well as the reduced potential for further productivity improvements might limit the potential returns for additional capital investment (Upchurch, 2018).

With regard to empirical investigations, Focacci (2021) compared the effects of increasing automation in China and Korea and concluded that robots did not always increase unemployment growth. In a similar study from Mexico, labour demand was increasing despite growing automation in jobs with a low and very low risk of automation (Ramos et al., 2022).

It follows that digital interconnectedness should not be thought of as an automatic job destroyer, but rather as a process which incorporates a complex interplay of different social and technological factors which transform work processes, change job profiles, and influence the demands which are put on industrial workers (Burstedde & Schirner, 2019).

## **2.2. Education & required qualifications**

Whether one views digital interconnectedness as an opportunity or a threat to industrial employment, it is widely acknowledged that lower-skilled and older workers are most vulnerable and likely to be displaced through the introduction of more complex work processes (Bellmann, 2017; Ramos et al., 2022; E. Weber, 2016). Due to the rising complexity of job profiles (Hecklau et al., 2016), new skills and a higher level of education will be demanded (Fareri et al., 2020; Freddi, 2018; Sallati et al., 2019). Accordingly, scholars argue that the aforementioned groups are least well-equipped to respond to changing job profiles by for instance, re-skilling (Grass & Weber, 2017; Hecklau et al., 2016). At the same time, the potential new jobs created through processes related to digital interconnectedness are likely to be filled by highly-skilled workers (Balsmeier & Woerter, 2019; Dachs et al., 2019; Shevyakova et al., 2021). Although widely assumed in the literature, the assumption that digital interconnectedness will polarise industrial employment by reducing low-skilled jobs and boosting high-skilled work should be treated with caution given the lack of empirical evidence for this dynamic (Becker & Spöttl, 2019; Hammershøj, 2019; Stettes et al., 2017). As already argued above, the way in

which digital interconnectedness impacts industrial employment differs across contexts which, in turn, should also hold for the way in which lower-skilled and older workers interact with and adapt to new work demands.

On the micro level, there are additional socio-economic but also individual factors that may hinder or support a successful introduction of digital interconnectedness. Fleming (2019) and Gallie (2017) are concerned that the broad application of digital technologies might eventually lead to intensified work and managerial control or even surveillance in highly automated companies. Following this line of argumentation, labour-use strategies were found to depend less on process technologies, but rather on the institutional framework and the role of the organization in introducing such new digital technologies or according processes (Krzywdzinski, 2017). D. A. Spencer (2018) argues that the threat workers associated with technological progress mainly comes from the erosion in the quality of work rather than from the loss of work. A study from Bulgaria supports this notion, by identifying the dehumanizing effects of automation, peer-pressure, and the individual self-perception of workers as being the main drivers of the fear of automation (Ivanov et al., 2020).

### **2.3. Company size**

Although digital interconnectedness is rising amongst industrial producers on the whole, there is a growing divide between digitally active firms and companies which have not yet begun digitalising their work processes (European Investment Bank, 2020). In particular, it would seem that larger companies are far more likely to be digitally interconnected than small- and medium-sized enterprises (SMEs) (ibid.). Research suggests that SMEs face more obstacles than larger firms (Horváth & Szabó, 2019) since they face higher financial constraints (Masood & Sonntag, 2020; Vrchota et al., 2019). Furthermore, SMEs' digital interconnectedness is often hampered by a lack of expertise and human resources (Basl, 2017; Horváth & Szabó, 2019). It follows that within a smaller organisational structure, it is more difficult to find people to drive the transformation of existing work processes (Vrchota et al., 2019). Finally, the adoption of digital solutions is made more complicated by the fact that the majority of technologies are developed by large companies which are less compatible with the specific needs and challenges of smaller firms (Masood & Sonntag, 2020; Mittal et al., 2018). Consequently, SMEs often lack a clear vision or strategy to incorporate digital technologies and approaches in their operations (Mittal et al., 2018). Another interesting distinction was identified by Shevyakova et al. (2021), who claim that larger companies pay special attention to technology and data-oriented topics, while SMEs focus more on customer-oriented processes and competences related to infrastructure and organization.

### **2.4. Hypotheses**

The first step in the analysis involves the assessment of workers' expectations of the impact of digital interconnectedness on industrial employment in the 2020 survey. In our analysis of the 2020 data, we expect to replicate the findings from the 2014 survey, namely that most workers expect staffing to decrease in manufacturing and assembly, but to increase in development – with required qualifications expected to

increase for all three, but mostly for development (Beier et al., 2017). This reflects research which asserts that increased digital interconnectedness will place higher demands on workers (Degryse, 2016) and that people working in less highly-skilled sectors are more at risk of being displaced (Fareri et al., 2020). The results of Beier et al. (2017) furthermore echo the claim that new employment opportunities through increased digital interconnectedness will likely be filled by highly-skilled workers (Balsmeier & Woerter, 2019; Dachs et al., 2019).

In the 2020 analysis, we additionally expect to confirm studies which show that larger companies tend to be more highly digitally interconnected than smaller ones. We base this hypothesis on the literature described in section 2.3, but also on studies on the role of company size on digital interconnectedness in Germany. Thus, although the level of digital interconnectedness amongst German industrial producers has increased in general, there remain discrepancies between companies which have significantly transformed their work processes and those which have not yet done so (Grebe et al., 2018; Heimisch et al., 2017; Schallow et al., 2018). Consequently, the level of digital interconnectedness amongst German industrial enterprises is strongly dependent on company size with larger companies tending to be more highly digitally interconnected than small- and medium-sized enterprises (Mertens et al., 2017; Schallow et al., 2018; Sommer, 2015).

For the comparative analysis, we consider that since 2014, German industrial producers have become more digitally interconnected (Staufen, 2018; T. Weber et al., 2018), as is evidenced by the fact that manufacturing industry-related robot density in Germany rose to 338 per 10,000 workers in 2018 – which indicates a 20% increase compared to 2014 (International Federation of Robotics, 2021). Although turnover in Germany's industrial sector grew by 10.2%, the level of industrial employment in Germany (as a percentage of total employment) decreased from 28.05% to 27.04% from 2014 to 2019 (World Bank, 2020). The fact that industrial employment has not changed substantially indicates that there has not been a fully-fledged transformation amongst German industrial producers. Rather, specific areas and existing work processes have undergone smaller changes which do not have substantial substituting effects on overall industrial employment (Behrendt et al., 2018; Franken et al., 2019). Regarding educational demands, there are indications that as opposed to drastically increasing these across the board, digital interconnectedness can increase, decrease, or else have a negligible effect on required qualifications in different contexts (Koch, 2017).

In addition to the view that developments in the German industrial sector since 2014 have perhaps been less drastic and more gradual than initially expected, it is important to keep in mind that the 2014 survey was conducted in a period where the hype around Industry 4.0 (Mertens et al., 2017) and predictions of mass technological unemployment through digitalisation (Frey & Osborne, 2017) – so-called 'end of work' scenarios – were far more prevalent in public discourses in Germany than today. Accordingly, a recent analysis of digitalisation discourses in Germany shows that the use of discursive frames emphasising the threat of digital interconnectedness has decreased in public debates (Buhr & Frankenberger, 2020). Given this normalisation of digital interconnectedness in public discourses, as well as the fact that we have not yet seen a rapid transformation of industrial employment in Germany, we hypothesise that the 2020 respondents will have more moderate expectations than the 2014 study participants.

### 3. Methodology and data

#### 3.1. Data collection

The first survey was conducted between November and December 2014, whereas data for the second survey was collected between November 2019 and June 2020. Both surveys were trialled twice and subsequently distributed to people working in the industrial sector in Germany via the online tool Limesurvey. We contacted our respondents directly via e-mail, through announcements in selected newsletters of renowned German industrial associations, as well as at conferences and other events. To make sure that we include one employee per company, we excluded responses which had identical answers with regards to company size, age, sector, and location. Overall, whereas 109 people participated in the 2014 survey, we reached 105 participants in 2020. The surveys are not identical although they do overlap in many questions (see the Appendix for the concrete structure of both questionnaires). The reason why we did not employ identical surveys is that certain survey items in 2014 proved to be less relevant either in the scientific debate of recent years (such as varying staffing requirements over the course of a project) or in the course of the discussions following the first survey (such as agreement with the provided definition of 'Digitalisation and Interconnectedness'). New questions were added in 2020 to allow for a more detailed analysis of the personal backgrounds of respondents (age, sex, position in the company) and to incorporate relevant factors that are often reflected in the literature (actual implementation level of 'Digitalisation and Interconnectedness' in the respective company). Respondents had the option to skip questions which is why in the analysis the sample sizes vary across the different survey items.

#### 3.2. Variables

We use four main indicators in the analysis. The first concerns people's expectations with regards to how staffing will be impacted by increased digital interconnectedness in their respective companies. Respondents were asked to record their expectations on a five-point scale ranging from 'substantial decrease' to 'substantial increase'. Respondents were asked to give their expectations on staffing for three departments, namely development, manufacturing, and assembly. By distinguishing between different domains, we analyse how expectations vary between more highly skilled sectors (development) and those which on average require less highly skilled workers (manufacturing and assembly). The next indicator is required qualifications where we used the same five-point scale to ask respondents how they feel that educational demands in development, manufacturing, and assembly will change through increased digital interconnectedness. The next main indicator is digital interconnectedness where we asked respondents to indicate the extent to which their companies' operations are digitally interconnected. We used a five-point scale ranging from no digital interconnection to full digital interconnection. Finally, we collected data on the company sizes by asking respondents to indicate how many people work in their respective companies.



### 3.3. Data analysis

Prior to conducting any statistical tests, the extreme categories of each five-point scale of the independent variables were pooled into a three-point scale, to prevent cells of the contingency tables from having too few observed counts. This not only increases the accuracy of statistical tests, but also reduces the degrees of freedom, which can increase their power (McDonald, 2014). However, even with the pooling, there were some cells that had very low or even no observed counts, which can bias the tests.

Each survey was then assessed for common methods bias (CMB) to calculate the potential influence of identical scales among varying questions. Two methods were employed to this end: Harmon's one-factor test and the unmeasured latent factor technique. The former is often used to detect CMB but is the subject of current debate whether it does so effectively and accurately (Aguirre-Urreta & Hu, 2019; Podsakoff et al., 2012; Schwarz et al., 2017). It involves the use of exploratory factor analysis to determine if a single factor in the dataset accounts for a majority (> 50%) of the variance in the data (Jordan & Troth, 2020). The latter takes a different approach using Confirmatory Factor Analysis (CFA) to assess the impact of an unmeasured latent factor that reflects the use of common methods. A well-fitting model with this factor thereby indicates presence of CMB (Jordan & Troth, 2020; Podsakoff et al., 2012).

In situations of low sample size ( $n < 1000$ ), which is the case in this study, it is often recommended to use Fisher's exact test to determine the significance of relationships (McDonald, 2014). However, a chi-squared test of independence can also be of use in such situations. The overall p-value might be less accurate, but it can provide useful information that Fisher's exact test cannot. Therefore, both tests were used to assess the significance of relationships between the independent and dependent variables used in this study. This combination allows for greater scrutiny of the significance of results and assurance in drawing further conclusions. Results of both tests are presented side-by-side in Tables 2–8 in Section 4 for direct comparison.

We primarily conducted a chi-squared test of independence on the contingency tables for each pair of variables. As the calculation of the chi-squared test statistic is disproportionately influenced by both too large and too small sample sizes (Bergh, 2015), a closer inspection of the contingency tables is required. Furthermore, comparing the observed and estimated expected frequencies on a cell-by-cell basis develops a closer understanding the nature of the relationship between the two variables (Agresti, 2018). As such, a cell-by-cell assessment of the standardized Pearson residuals was completed for each contingency table at a significance level of 0.05. For those cells in which the standardized residual exceeds the test statistic of the normal distribution corresponding to a 0.05 significance level (1.96), two statements can be made (Sharpe, 2015):

- 1) They show a greater discrepancy than would be expected if the variables were truly independent.
- 2) There is a lack of fit of the null hypothesis ( $H_0$ ) in that cell; i.e the variables are NOT independent.

Those variables with enough cells that supported the alternative hypothesis were deemed to be NOT independent of the dependent variable, indicating the presence of an underlying relationship.



In addition, Fisher’s Exact Test was used to assess the independence of relationships between the independent and dependent variables. This test does not allow for a cell-by-cell assessment of the contingency tables and therefore produces only an overall p-value. Alongside the p-values from the Chi-squared test of independence and the cell-by-cell analysis of standardized residuals, the Fisher’s exact test p-values were then interpreted in the context of Industry 4.0 as laid out in the introduction. In this regard, we are aware of the critique that Fisher’s test is a conservative method to test the independence of two variables and that a small sample size can affect the significance of results of both tests (Agresti, 2018), and are therefore cautious in our interpretation of the results.

**3.4. Limitations**

In the first survey, data on respondents’ sex, age, and position within the company were not collected, as well as information on the type of production their companies engage in. We therefore cannot examine the extent to which these personal and company-level characteristics influence people’s perceptions. A further limitation is that for most of the survey items, the number of answers recorded in the 2020 sample is higher than in 2014. We therefore need to consider the possibility that potentially more moderate results in 2020 reflect a regression to the mean. Furthermore, with regards to company size, there are more large companies (>5,000 employees) in the 2014 sample than in the 2020 sample (see, Table 1). Since the literature holds that large companies tend to be more highly digitally interconnected (Horváth & Szabó, 2019; Masood & Sonntag, 2020), we aggregate the comparative data on staffing and required qualifications by company size to assess whether the developments from 2014 to 2020 are mainly caused by the fact that the 2020 sample includes fewer larger companies. Last, neither sample is large enough for statistical tests to have significant strength and generalizability. For this to be possible, the sample would have needed to be an order of magnitude larger. However, the results presented here were produced with appropriate statistical tests and can be taken as preliminary evidence for the trends described in this study.

**4. Results & discussion**

**4.1. 2014 Study**

**4.1.1. Staffing**

Expected changes to staffing requirements in 2014 varied across the three sectors of development, manufacturing, and assembly (Table 2). Of these, only the manufacturing sector had significant results, with respondents from larger companies (>5,000 employees) expecting fewer positions due to digital interconnectedness. Significantly more

**Table 1.** Percent share of respondents from various company sizes from both sample.

	2014 study (n = 88)	2020 study (n = 105)
<250 employees	34%	37%
250–5,000 employees	18%	28%
>5,000 employees	48%	35%

**Table 2.** Results of the Chi-squared test of Independence and Fisher's exact test for the relationship between expected changes in staffing requirements for a) development, b) manufacturing, and c) assembly, and company size in 2014. In each cell are (from top to bottom) the observed and expected counts, followed in parentheses by the standardized residuals. Statistically significant cells are bolded.

Categories	Development (n = 63)			Manufacturing (n = 48)			Assembly (n = 46)		
	Fisher's p = 0.47	Chi-squared p = 0.38		Fisher's p = 0.04	Chi-squared p = 0.05		Fisher's p = 0.12	Chi-squared p = 0.06	
	1/2 - less	3 - no change	4/5 - more	1/2 - less	3 - no change	4/5 - more	1/2 - less	3 - no change	4/5 - more
<250	0 0.5 (-0.84)	3 3.3 (-0.22)	13 12.2 (0.55)	5 5.2 (-0.19)	3 3.2 (-0.14)	1 0.6 (0.67)	6 4.9 (0.83)	3 3.7 (-0.54)	0 0.4 (-0.71)
250–5,000	0 0.4 (-0.77)	5 2.9 (1.58)	9 10.7 (-1.19)	3 6.4 <b>(-2.38)</b>	8 3.9 <b>(2.95)</b>	0 0.7 (-0.98)	3 5.4 (-1.75)	5 4.1 (0.63)	2 0.4 <b>(2.74)</b>
>5,000	2 1 (1.37)	5 6.8 (-1.13)	26 25.1 (0.51)	20 16.3 <b>(2.18)</b>	6 9.9 <b>(-2.4)</b>	2 1.8 (0.3)	16 14.7 (0.8)	11 11.2 (-0.09)	0 1.2 (-1.72)

respondents from medium companies (250–5,000 employees) expected no change in the number of manufacturing positions. In the assembly and development sectors, no significant relationships were identified. However, the vast majority of respondents from all company sizes expected more positions to be created in the development sector. This implies that, while there is no relationship between company size and perceived changes to staffing requirements, most respondents believed that more positions in development will be created through digital interconnectedness.

#### 4.1.2. Required qualifications

For expected changes to qualification requirements, no significant relationships were identified across all three sectors (Table 3). However, as with the perceived changes to staffing in the development sector, respondents from all company sizes overwhelmingly expected higher qualification requirements in development. Of the 64 respondents to this question, only six believed that there would either be no change or lower requirements.

**Table 3.** Results of the Chi-squared test of Independence and Fisher's exact test for the relationship between expected changes in qualification requirements for a) development, b) manufacturing, and c) assembly, and company size in 2014. Formatting as with Table 2.

Categories	Development (n = 64)			Manufacturing (n = 54)			Assembly (n = 53)		
	Fisher's p = 0.23	Chi-squared p = 0.31		Fisher's p = 0.55	Chi-squared p = 0.49		Fisher's p = 0.60	Chi-squared p = 0.55	
	1/2 - lower	3 - no change	4/5 - higher	1/2 - lower	3 - no change	4/5 - higher	1/2 - lower	3 - no change	4/5 - higher
<250	1 0.3 (1.55)	0 1.5 (-1.51)	18 17.2 (0.73)	4 2.2 (1.57)	1 2.4 (-1.15)	8 8.4 (-0.28)	4 2.2 (1.52)	3 4.9 (-1.26)	6 5.9 (0.07)
250–5,000	0 0.2 (-0.53)	2 1.1 (1.02)	12 12.7 (-0.71)	1 2 (-0.88)	3 2.2 (0.66)	8 7.8 (0.15)	1 1.9 (-0.78)	5 4.2 (0.59)	5 5 (0.01)
>5,000	0 0.5 (-0.98)	3 2.4 (0.54)	28 28.1 (-0.08)	4 4.8 (-0.61)	6 5.4 (0.44)	19 18.8 (0.12)	4 4.9 (-0.68)	12 10.9 (0.6)	13 13.1 (-0.07)

In manufacturing and assembly, though no significant relationships were identified, this might reflect upon the greater uncertainty surrounding the future of these sectors in 2014. In manufacturing, while the tendency was for respondents from all companies to expect higher qualification requirements, responses were spread out enough for no significant relationship to be identified.

**4.1.3. Future intelligent assistance**

In 2014, respondents from all company sizes expected an increase in the amount of intelligent assistance in their daily work routines (Table 4). As with previous variables, this overwhelming perception skewed the contingency table and prevented any statistical significance from being achieved. In other words, no relationship between company size and expected changes in intelligent assistance was identified, but the large majority of respondents expect an increase. No respondents expected less intelligent assistance and only seven of 71 respondents expected no change.

**4.2. 2020 Study**

**4.2.1. Staffing**

Our data on staffing (Table 5) mirrors the finding in the literature that increased digital interconnectedness in industrial production will create more opportunities for highly-skilled workers (Bonekamp & Sure, 2015; Krzywdzinski, 2017). Significantly more respondents from large companies (>5,000) expected there to be fewer employees required in manufacturing and assembly, whereas significantly more respondents from smaller companies (<250) expected no change in staffing requirements in these sectors. For the development sector no significant relationship was detected, though the tendency was to expect more employees in this sector for medium (250–5,000) and large companies. No significant relationship between company size and perceived changes to staffing requirements was seen for medium size companies. When we consider manufacturing and assembly mainly as lower or medium skilled work, our data would support the claim that the perceived expectations are for this employment to decrease in large companies only. In small companies, respondents expect no change and the results for medium companies are inconclusive. This partially supports research contradicting the claim that lower-skilled and

**Table 4.** Results of the Chi-squared test of Independence and Fisher’s exact test for the relationship between expected changes in intelligent assistance and company size in 2014. Formatting as with Table 2.

Future Intelligent Assistance n = 71 Categories	Fisher’s p = 0.25 3 – no change	Chi-squared p = 0.26 4/5 – more
<250	2 2.4 (–0.31)	22 21.6 (0.31)
250–5,000	3 1.4 (1.62)	11 12.6 (–1.62)
>5,000	2 3.3 (–1.00)	31 29.7 (1.00)



that increased digital interconnectedness will place more demands on highly-skilled workers (Balsmeier & Woerter, 2019; Dachs et al., 2019). However, the findings are more nuanced than for staffing since there is a less clear-cut difference in the data between development and manufacturing, as well as between large and small companies. The fact that the respondents are more split in their opinions on qualifications than in staffing echoes the arguments of scholars who claim that rather than automatically increasing required qualifications across the board, depending on the context and the company, digital interconnectedness can increase, decrease, or else have no substantial impact on required qualifications in industrial production (Koch, 2017). On a similar notion, a study by Dhondt et al. (2021) showed only small effects of technological change on changing skills use, but larger effects by the changing working environment, while the concept of bounded automation by Fleming (2019) suggests the pace of digitalisation is constrained by the ‘price of labour, organisational power relations and the nature of the task itself’.

#### 4.2.3. Future intelligent assistance & level of digital interconnectedness

The aggregated data on digital interconnectedness supports the assertion that larger companies have a higher level of digital interconnectedness (Horváth & Szabó, 2019; Masood & Sonntag, 2020). As can be seen in Table 7, significantly more respondents from small companies perceive their company as not digitally interconnected, whereas for large companies, significantly more perceive their company as either interconnected or were neutral in their opinion. For respondents from medium companies, significantly less found their company to be interconnected and an almost significant number found their company to be not interconnected. In addition, Table 8 shows that significantly more respondents from small companies believe that there will be no change in the level of intelligent assistance in their workplace in the next 5 years. No significant trend is seen for respondents from medium companies, but significantly more respondents from large companies expect the level of intelligent assistance to increase in the next 5 years.

### 4.3. Comparative analysis: 2014 & 2020 data

#### 4.3.1. Staffing

Table 9 indicates that for development, expectations have flattened with a lower rate of respondents expecting higher levels of employment in 2020 (61%) than in 2014 (77%). 20% expected no changes in 2014 with the rate increasing to 34% in

**Table 7.** Results of the Chi-squared test of Independence and Fisher’s exact test for the relationship between perceived level of digital interconnectedness and company size in 2020. Formatting as with Table 2.

Perceived Digital Interconnectedness n = 95 Categories	Fisher’s p < 0.005		Chi-squared p < 0.005
	1/2 not interconnected	3	4/5 interconnected
<250	22 13.1 <b>(3.97)</b>	5 10.8 <b>(–2.65)</b>	4 7.2 <b>(–1.65)</b>
250–5,000	16 11.8 (1.92)	10 9.7 (0.13)	2 6.5 <b>(–2.39)</b>
>5,000	2 15.2 <b>(–5.64)</b>	18 12.5 <b>(2.44)</b>	16 8.3 <b>(3.84)</b>

**Table 8.** Results of the Chi-squared test of Independence and Fisher's exact test for the relationship between expected changes in intelligent assistance and company size. Formatting as with Table 2.

Future Intelligent Assistance n = 86 Categories	Fisher's p < 0.005 1/2 – less	Chi-squared p < 0.005 3 – no change	4/5 – more
<250	1 0.3 (1.45)	11 4.9 <b>(3.71)</b>	16 22.8 <b>(-4.02)</b>
250–5,000	0 0.3 (-0.63)	3 4.2 (-0.75)	21 19.5 (0.91)
>5,000	0 0.4 (-0.81)	1 5.9 <b>(-2.87)</b>	33 27.7 <b>(3.02)</b>

**Table 9.** Staffing requirements in differently sized companies (2014 & 2020 data).

Company size	Responses	Development		Manufacturing		Assembly	
		2014 (n = 63)	2020 (n = 89)	2014 (n = 48)	2020 (n = 84)	2014 (n = 46)	2020 (n = 84)
Overall	Lower	3%	4%	58%	37%	54%	37%
	No changes	20%	34%	35%	55%	41%	55%
	Higher	77%	61%	7%	8%	5%	8%
<250 employees	Lower	0%	6%	56%	15%	67%	7%
	No changes	19%	44%	33%	77%	33%	82%
	Higher	81%	50%	11%	8%	0%	11%
250–5,000 employees	Lower	0%	4%	27%	36%	30%	38%
	No changes	36%	27%	73%	52%	50%	58%
	Higher	64%	69%	0%	12%	20%	4%
>5,000 employees	Lower	6%	3%	71%	54%	59%	57%
	No changes	15%	29%	21%	39%	41%	41%
	Higher	79%	67%	7%	6%	0%	3%

2020. We see a similar trend for manufacturing and assembly. For manufacturing, the rate of respondents expecting decreased staffing fell from 56% to 37%. At the same time, respondents expecting no changes rose from 36% to 55%. In assembly, 34% of the survey participants expected drops in employment in 2020 compared to 53% in 2014. The rate expecting no significant changes to staffing in their respective company rose from 40% to 60%. As such, the data indicate that people expect a less substantial impact on staffing through increased digital interconnectedness. However, as mentioned above, due to the too small sample size of the 2014 data set we cannot verify this assumption through statistical testing and we also need to control for whether the higher expectations in 2014 are linked to the fact that there are more large companies in the 2014 sample than in the 2020 data. For companies with more than 5,000 employees, we see that expectations have decreased for development and manufacturing and roughly stayed the same for assembly. The rate of respondents working for companies with less than 250 employees who expect no substantial changes is considerably higher in 2020 in all three departments. For the firms with less than 5,000 employees, the results are more mixed.

4.3.2. Required qualifications

Our data shows, that expectations for higher required qualifications due to digital interconnectedness remain on similarly high levels in 2020 compared to the 2014 data. The only major shift can be found for the development domain, where we see a rise in the rate of people expecting no changes (from 7% to 25%) at the expense of the proportion of respondents expecting higher qualification levels. A much more moderate rise in the rate of people expecting no changes can be seen in manufacturing (from 18% to 24%), with the data on assembly hardly changing at all. In development, the vast majority of employees still expects an increase in required qualifications due to digital interconnectedness (see, Table 10). Whereas 91% expected higher required qualifications in 2014, this value lies at 75% in the 2020 sample. Interestingly, whereas the aggregated data for larger companies (>5,000 employees) remains largely unchanged in development, we see that expectations have flattened significantly there for smaller companies (<250 employees) but increased significantly for companies with more than 250 workers. This flattening of expectations for smaller companies (<250 employees) can also be seen in a more moderate form in manufacturing (−12 percentage points) and assembly (−9 pp.). A moderate increase regarding the required qualifications due to digital interconnectedness can be observed for manufacturing and assembly for companies with more than 250 workers as well as for larger companies (>5,000 employees).

4.4. Common method bias

Using both Harman’s one factor technique and the unmeasured latent factor technique, no evidence of CMB was identified. Harman’s technique yielded a single factor accounting for 37% and 30% of the variance in the 2014 and 2020 surveys, respectively, below the 50% threshold. CFA models built using a single unmeasured latent factor were found to not explain a significant portion of variance. While in both cases the chi-square test of significance had p-values lower than 0.005, these are likely influenced by sample size and cannot be trusted, as explained previously. The Comparative Fit Index (CFI) was 0.38 and 0.48 for the 2014 and 2020 models, respectively. Typically, a CFI > 0.95 is considered good fit (Van Laar & Braeken, 2021). Therefore, we deem CMB to not influence the results of these two surveys.

Table 10. Required qualifications in differently sized companies (2014 & 2020 data).

Responses		Development		Manufacturing		Assembly	
		2014 (n = 64)	2020 (n = 92)	2014 (n = 54)	2020 (n = 85)	2014 (n = 53)	2020 (n = 84)
Overall	Lower	2%	0%	17%	9%	17%	15%
	No changes	7%	25%	19%	24%	38%	36%
	Higher	91%	75%	65%	67%	45%	49%
<250 employees	Lower	5%	0%	31%	8%	31%	11%
	No changes	0%	42%	8%	42%	23%	52%
	Higher	95%	58%	62%	50%	46%	37%
250–5,000 employees	Lower	0%	0%	8%	8%	9%	13%
	No changes	57%	19%	25%	23%	45%	33%
	Higher	43%	71%	67%	69%	45%	54%
>5,000 employees	Lower	0%	0%	14%	12%	14%	21%
	No changes	10%	13%	21%	9%	41%	24%
	Higher	90%	87%	66%	79%	45%	55%



## 5. Discussion & conclusions

Our empirical analysis substantiates the claim that increased digital interconnectedness will provide more employment opportunities for highly skilled employees whilst people working in manufacturing and assembly are more susceptible to job losses. Having said that, the significant number of respondents expecting no changes to staffing in manufacturing and assembly undermines research which predicts mass technological unemployment through digital interconnectedness. Future research in this area should focus on additional socio-economic factors that might influence the magnitude of this expected transformation of the workforce. Additionally, the direct and indirect effects of Industry 4.0 on staffing requirements should be investigated in the light of the global fragmentation of production. Practitioners should start assessing the potentially mediating effects that digital assistance systems could provide in order to be able to employ effectively working personnel, especially in the manufacturing and assembly sectors, who are not overwhelmed by permanently working with digitally interconnected solutions.

Our study furthermore confirms the assertion that larger firms have a higher level of digital interconnectedness and are thus also more likely to experience changes to staffing and required qualifications. The most intriguing finding of the paper is that workers' predictions of how digital interconnectedness will impact industrial employment have become more moderate since fewer workers expect substantial job losses in manufacturing and assembly. However, due to the fact that we could not statistically substantiate this assumption, we suggest to research this causality more extensively and for different countries in future studies. At this point in time, we hypothesise that since there have been no substantial job losses in industrial employment in Germany since 2014 – and since the public discourse around digitalisation is less centred on the threat of mass technological unemployment – workers' expectations have become more moderate. We may also draw a parallel to socio-technical studies which emphasise that increases in digital interconnectedness occur gradually and are highly dependent on human agency. Thus, it may also be suggested that, as workers have become more familiar and gain more experience with digital technologies in their work environment, they also realise that digital transformations do not occur in a vacuum, but are inherently dependent on the cooperation and acceptance of human workers.

Overall, the significance of our analysis has limitations. First, for the comparative analysis, we only control for company size and do not consider how differences in personal and company characteristics determine the differences between the two samples. At the same time, for multiple variables, we recorded more answers for the second study than for the first. It can thus be argued that the more moderate answers in the 2020 data are reflective of a regression to the mean. In addition, while both Fisher's test and a Chi-squared test of independence were performed and showed good agreement, the small sample size of both studies substantially impacted the generalizability of the results, and this should be considered a major limitation of this work. These results do, however, serve as preliminary evidence of the trends we discuss in this paper. These limitations do not disprove our conclusions but do urge caution when interpreting the findings. Accordingly, whilst the findings indicating the role of company size and the fact that digital interconnectedness creates more

opportunities for highly-skilled workers are replicated in other studies, the assertion that people are less likely to expect substantial changes once becoming more familiar with digital interconnectedness should be investigated further. Accordingly, quantitative work with larger sample sizes would enable the use of more advanced statistical measures to investigate our findings. Furthermore, our research should certainly be complemented by qualitative studies using interviews or focus groups with industrial workers to better understand how perceptions on digital interconnectedness have changed. In this regard, it would also be useful to better understand how employees' opinions and views on digitalisation are formulated in the first place and to what extent familiarity with digitalisation and practical experience play a role.

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## Appendix: Structure of Questionnaires

2014 Study	2020 Study
<b>Introduction</b>	
Text explaining the concept “Digitalisation and Interconnectedness”	Text explaining the concept “Digitalisation and Interconnectedness”
Q: Do you agree with this definition?	-
<ul style="list-style-type: none"> <li>• Yes</li> <li>• No [Reasoning]</li> </ul>	
<b>Personal data</b>	
-	Q: Age:
-	Q: Sex:
-	Q: Position of respondent:
	<ul style="list-style-type: none"> <li>• Management level</li> <li>• Operational level</li> <li>• Other: [please specify]</li> </ul>
Q: How familiar are you with the concept of ‘Digitalisation and Interconnectedness’?	-
<ul style="list-style-type: none"> <li>• Very familiar (‘expert’)</li> <li>• Familiar</li> <li>• Not very familiar (‘layperson’)</li> <li>• Never heard of this before</li> <li>• No answer</li> </ul>	
Q: In which domain do you work?	Q: In what area/department do you work?
<ul style="list-style-type: none"> <li>• Development</li> <li>• Manufacturing</li> <li>• Assembly</li> <li>• Quality management</li> <li>• Other: [please specify]</li> </ul>	<ul style="list-style-type: none"> <li>• Development</li> <li>• Manufacturing</li> <li>• Administration</li> <li>• Marketing</li> <li>• Other: [please specify]</li> </ul>
<b>Company data</b>	
Q: In what sector is your company active?	Q: In what sector is your company active?
<ul style="list-style-type: none"> <li>• Automotive industry</li> <li>• Mechanical and plant engineering</li> <li>• Information and communication technology</li> <li>• Electronics</li> <li>• Other: [please specify]</li> </ul>	<ul style="list-style-type: none"> <li>• Automotive industry</li> <li>• Mechanical and plant engineering</li> <li>• Information and communication technology</li> <li>• Electronics</li> <li>• Other: [please specify]</li> </ul>
Q: How many employees (E) does your company have?	Q: How many employees (E) does your company have?
<ul style="list-style-type: none"> <li>• &lt;250E</li> <li>• 250–5,000 E</li> <li>• &gt;5,000 E</li> </ul>	<ul style="list-style-type: none"> <li>• &lt;250E</li> <li>• 250–5,000 E</li> <li>• &gt;5,000 E</li> </ul>
-	Q: To what extent has your company implemented the concept of ‘Digitalisation and Interconnectedness’ so far?
	<ul style="list-style-type: none"> <li>• 5-point Likert-type scale</li> <li>1 – Not digitally interconnected</li> <li>...</li> <li>5 – Fully digitally interconnected</li> <li>• Don’t know</li> <li>• No answer</li> </ul>
<b>Future of Work</b>	
Q: How will ‘Digitalisation and Interconnectedness’ affect staffing requirements in your company? Please assess for each of the three domains development, manufacturing, assembly respectively.	Q: How will ‘Digitalisation and Interconnectedness’ affect staffing requirements in your company? Please assess for each of the three domains development, manufacturing, assembly respectively.
The company will require:	The company will require:
<ul style="list-style-type: none"> <li>• 5-point Likert-type scale</li> <li>1 – Far more workers</li> <li>2 – More workers</li> <li>3 – No change expected</li> <li>4 – Less workers</li> <li>5 – Far less workers</li> <li>• N/A</li> </ul>	<ul style="list-style-type: none"> <li>• 5-point Likert-type scale</li> <li>1 – Far less workers</li> <li>2 – Less workers</li> <li>3 – No change expected</li> <li>4 – More workers</li> <li>5 – Far more workers</li> <li>• Don’t know</li> <li>• No answer</li> </ul>

(Continued)

(Continued).

2014 Study	2020 Study
<p>Q: Depending on the particular phase of a development project, staffing requirements may vary considerably over the course of a project. Please assess for each of the three domains development, manufacturing, assembly respectively.</p> <p>What effect will 'Digitalisation and Interconnectedness' have on this aspect of your company's work?</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Significantly greater variations</li> <li>2 – Greater variations</li> <li>3 – No change expected</li> <li>4 – Less variations</li> <li>5 – Significantly less variations</li> </ul> </li> <li>• N/A</li> </ul> <p>Q: To what extent will 'Digitalisation and Interconnectedness' affect the qualifications that your company requires of its employees? Please assess for each of the three domains development, manufacturing, assembly respectively.</p> <p>The required qualifications will become ...</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Considerably more sophisticated</li> <li>2 – Slightly more sophisticated</li> <li>3 – No change expected</li> <li>4 – Less sophisticated</li> <li>5 – Considerably less sophisticated</li> </ul> </li> <li>• N/A</li> </ul> <p>Q: In your opinion, what effect will 'Digitalisation and Interconnectedness' have on work intensification in the next ten years? In future, the number of tasks performed at the same time will be:</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Significantly greater</li> <li>2 – Slightly greater</li> <li>3 – No change expected</li> <li>4 – Slightly less</li> <li>5 – Significantly less</li> </ul> </li> <li>• N/A</li> </ul> <p>Q: How often will your employees be supported in complex tasks by intelligent assistance systems in the future (e.g. by explanatory software on tablets or per head-mounted display)?</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Much more often</li> <li>2 – More often</li> <li>3 – No change expected</li> <li>4 – Less often</li> <li>5 – Much less often</li> </ul> </li> <li>• N/A</li> </ul> <p>Q: What do you think about the impacts on the employees' work due to the increasing digitalisation of processes?</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Their work has become much more complex and stressful</li> <li>2 – Their work has become slightly more complex and stressful</li> <li>3 – No change</li> <li>4 – Their work has become less complex and stressful</li> <li>5 – Their work has become much less complex and stressful</li> </ul> </li> <li>• N/A</li> </ul>	<p>Q: To what extent will 'Digitalisation and Interconnectedness' affect the qualifications that your company requires of its employees? Please assess for each of the three domains development, manufacturing, assembly respectively.</p> <p>The required qualifications will become ...</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Much lower</li> <li>2 – Lower</li> <li>3 – No change expected</li> <li>4 – Higher</li> <li>5 – Much higher</li> </ul> </li> <li>• Don't know</li> <li>• No answer</li> </ul> <p>Q: How often will your employees be supported in complex tasks by intelligent assistance systems in the next five years (e.g. by explanatory software on tablets or per head-mounted display)?</p> <ul style="list-style-type: none"> <li>• 5-point Likert-type scale <ul style="list-style-type: none"> <li>1 – Much less often</li> <li>2 – Less often</li> <li>3 – No change expected</li> <li>4 – More often</li> <li>5 – Much more often</li> </ul> </li> <li>• Don't know</li> <li>• No answer</li> </ul>