Development of a Job-Exposure Matrix (JEM) based on the BIBB/BAuA Employment Survey 2018

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baua: Focus

The publication at hand develops a job-exposure matrix based on the data of the BIBB/BAuA Employment Survey 2018 that assigns each occupation with levels of exposure for different job demands. The JEM comprises five different categories (physical and environmental job demands, work intensity, working time location, and autonomy). Another category for social support was initially also analysed, but not included in the JEM due to the low variation between occupations. The JEM is made available for different occupational classifications (the German Classification of Occupations [KldB] 1992, ISCO 2008).

Content

1 Introduction

The aim of monitoring working conditions is to describe employees and their working situation as detailed as possible. It is particularly important to identify those groups within the working population who are exposed to increased health risks due to certain (constellations of) working conditions and/or physical and psycho-social strain. Established occupational classifications (e. g., KldB, ISCO) can be used to group occupations on different levels of hierarchy. However, such classifications do not produce groups that are homogenous in terms of exposure, i. e., groups that are similar to each other regarding the level of exposure they experience in the workplace. A so-called job-exposure matrix (JEM) is a promising way to depict exposure profiles for different occupations. A JEM comprises suitable types of workplaces (e. g., occupations) in the rows and exposure characteristics (e. g., working conditions) in the columns. Each cell represents the exposure values of each type of workplace regarding the type of exposure (see, e. g., Nübling et al. 2017, Latza & Seidler 2017, Taeger 2017). JEMs can thus be used to identify typical exposure constellations for occupations.

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The more homogeneous the members of a group are regarding their respective exposure, the higher the quality of the JEM (Nübling et al. 2017, Taeger 2017). Consequently, exposure variability within an (occupational) group is lost as a result of this construction because the same values are assigned to all employees of the same group. This can lead to inaccurate exposure assessment, in particular, when the variation in exposure cannot be sufficiently attributed to the selected workplace characteristic (occupational groups) (Nübling et al. 2017, Peters 2020). Nevertheless, a JEM yields more objective measurements of occupation-specific exposures, one that reduces bias compared to individual self-assessment/self-reported individual indicators (reporting bias) (Niedhammer et al. 2020). Another significant advantage of JEMs is the possibility to merge (aggregated) job exposures with other datasets (e.g., health care data), which do not feature information on individual job exposure and job tasks, using occupational classifications. This helps to expand the opportunities for research on the association of job exposures and health and opens up new research questions relating to the world of work.

The BIBB/BAuA Employment Survey and its preceding surveys have been used to calculate JEMs in the past. As part of the BAuA research project "Costs of work-related illnesses" (published as Fb 946), for example, Bödeker et al. (2002) developed a JEM using the BIBB/IAB Employment Survey 1998 to assess the effects of work demand factors on illnesses and the costs resulting from them. To do so, they determined the share of all work-related diseases for seven individual exposure factors as well as an additional factor summarising physical and mental strain. The JEM that was constructed was also used in analyses on occupational disability and early retirement (Bödeker et al. 2006, Dragano 2014).

Kroll (2011, 2015) has also calculated JEMs based on the BIBB/BAuA Employment Surveys of 2006 and 2012, which can be retrieved via GESIS.[1] Both Bödeker and Kroll include various individual items that they (at least partially) group together into factors. The JEM developed by Kroll uses the most information. In it, two individual indices are formed from which an overall index can be calculated. In addition to an index for physical demands, which includes ergonomic and environmental job demands, it groups together psycho-social demands (mental and time pressure-related demands coupled with a lack of resources) in one index. Overall, the JEM developed by Kroll (2011) has shown to be (externally) valid and has been used in the context of different research questions and with different datasets (pension insurance data, Mikrozensus) (e.g., Brussig 2014; Meyer & Künn-Nelen 2014).

The aim of the publication at hand is to develop a JEM based on the current BIBB/BAuA Employment Survey 2018. The empirical approach used here is based on the procedure used by Kroll (2011, 2015) that estimates occupation-specific exposure indices using a linear multi-level model. This approach makes it possible to control for intervening variables (age, sex, working time) and, additionally, takes the hierarchical structure of occupational classifications into account, delivering more robust estimators, especially for rare occupations. In contrast to Kroll, the aim here is to depict working conditions in a more differentiated way across different individual categories in order to represent occupation-specific working conditions in as much detail as possible. When summarising many different working conditions in one index – in the way done by Kroll, for example, with mental strain, lack of resources, and working time-related demands – there is a risk of biased results because certain working conditions might cancel each other out. The publication at hand therefore derives its categories from established occupational stress theories from occupational health psychology, such as the Job Demands-Resources model (JD-R, Demerouti et al. 2001).[2]

1 To be found at: *https://data.gesis.org/sharing/#!Detail/10.7802/1102*

2 It should also be kept in mind that the BIBB/BAuA Employment Survey does not survey established scales like the ones established in the Job Content Questionnaire (JCQ, Karasek et al. 1998). Instead, the individual surveyed items, which are based on concepts of occupational stress theories in occupational health psychology, are assigned to the categories.

The criteria to be analysed were selected based on the criteria examined in BAuA's Stress Report Germany (Lohmann-Haislah 2012), whereby particular care was taken to cover the key factors of work design as identified in the BAuA project "Mental Health in the Working World" (cf. Rothe et al. 2017). Specifically, different categories of job demands (physical, environmental, work intensity, working time location) and resources (autonomy, social support) were treated as stand-alone indices. The developed JEM is made available as a separate Excel file for the different levels of hierarchy of the occupational classifications ISCO 2008 and KldB 1992. In order to be able to use the values of the JEM for subsequent analyses with other data, they must be merged with the respective dataset using the variable of the respective occupational classification. Due to its structure, the KldB 2010 classification is not suitable for constructing a JEM in the way done here. Unlike other classifications, the KldB 2010 only begins to differentiate between four different requirement levels based on complexity at the fifth digit.

The main distinguishing feature at higher levels is the so-called occupational expertise, which results in employees with different requirement levels being grouped together, e. g., the engineer designing the car and the worker assembling this car are featured in the same 3-digit group. However, the working conditions of these two occupational groups differ substantially, making it inevitable to include this level of hierarchy. The hierarchical construction of the JEM would involve considering all 1,286 5-digit groups, which, for a dataset with a total of 20,000 respondents, inevitably leads to very small case numbers in some cells, resulting in inaccurate estimates. The fact that most areas do not feature all requirement levels, and some of the groups, particularly for unskilled activities, are very small, also rules out constructing separate JEMs by requirement level.

Unlike the method chosen here, Kroll (2015) also accounts for the various levels of the KldB 2010 in the JEM. When calculating the exposure indices in the multi-level model – as in other occupational classifications – the 2, 3, and 4-digit groups are treated as levels. Additionally, however, the requirement level is included as a control variable (in the form of dummy variables). Lastly, the estimators of these requirement level dummies are included for the predicted exposure values of the 5-digit groups. While this makes it possible to produce adjusted exposure values for the 5-digit groups, it still is not possible to differentiate between the different requirement levels at a higher aggregated level (2, 3, 4-digit groups), which is largely due to the way KldB 2010 is constructed.

2 Data

The BIBB/BAuA Employment Survey 2018 is a recurring and representative cross-sectional survey of around 20,000 employees in Germany (Gensicke & Tschersich 2018). The survey includes individuals in employment aged 15 years and older who work at least 10 hours of paid work a week on a regular basis. To gain information on the job demands of these employees, physical and mental job demands, and resources were surveyed using a multitude of variables.

Different categories of demands and resources were included in calculating the JEM based on occupational stress models in occupational health psychology (including Karasek 1979, Demerouti et al. 2001). Among the job demands included are physical and environmental demands as well as work intensity and demands relating to working time location. Scales for autonomy and social support in the workplace are generated as resources. In total, 29 items were selected and assigned to the various categories (cf. Table 1). Compared to Kroll (2011, 2015), the job demands are considered in a more differentiated way, also to avoid bias resulting from aggregation.

For the analyses, employees aged 15–65 years are considered, whereby self-employed and freelancers are excluded.[3] Moreover, only individuals with valid information for the considered variables are included.

3 Empirical approach

The empirical approach is based on Kroll (2011, 2018), who developed and constructed the job demand indices for earlier BIBB/BAuA employment surveys.[4] This approach deviates from the conventional method for calculating job-exposure matrices (JEMs), which are often based on the occupation-specific mean values for the respective physical and psycho-social exposures. This is problematic, however, because the implicit assumption is that differences in the observed exposure are exclusively due to occupational differences. Calculating occupational exposure using a linear multi-level model (random intercept) yields more robust estimators, especially for rarer occupations, and allows for the control of various variables (e. g., sex, age, weekly working hours). Multi-level models with random intercepts take into account the nested structure of the data – in this case, individuals who are nested in occupations – by dividing the total error term into a separate random error term per level. These analyses use the entire hierarchical structure of the occupational classifications by considering three levels for the 2, 3 and 4-digit groups in an occupational classification (see Kroll 2011, Meyer & Künn-Nelen 2014):

$$Y_{i,\,j1,\,j2,\,j3} = \beta_0 + u_{j1} + u_{j2} + u_{j3} + \beta_x X_i + \varepsilon_i$$

The total variance of job demands is thus divided into the variance attributable to occupation-specific characteristics of the 2-digit groups (u_{j1}), variance attributable to differences between occupations at the 3-digit level (u_{j2}), variance attributable to differences between occupations at the 4-digit level (u_{j3}), and, finally, the residual variance (ε_i), attributable to other, e. g., individual characteristics (Rabe-Hesketh and Skrondal 2008). By including the control variables ($\beta_x X_i$), the occupational level-specific intercepts thus represent the part of the variance between occupations that is not attributable to differences in these control variables. It is thus assumed that the respective working condition $Y_{i,j1,j2,j3}$ of the individual i in the occupational level j (j_1 for the 2-digit, j_2 for the 3-digit and j_3 for the 4-digit group) is the sum of the parameters for the general job demand (β_0, overall mean), the occupation-specific demand at the different levels of the occupational classification of the 2, 3, 4-digit groups (u_{j1}, u_{j2}, u_{j3}), a vector of control variables ($\beta_x X_i$) and the individual residual error term (ε_i).

Thus, a major advantage of this empirical approach is that group effects (i. e., those due to different occupations) and individual effects are taken into account separately. Owing to this specific construction, it is possible to extract more "objective" measurements for job demands, which are attributable to differences in occupations and less to individual characteristics. Contrary to Kroll (2011, 2015), who summarises different demands in three overall scores (physical, psycho-social, total), the publication at hand looks at six categories. Exposure indices are calculated in several steps based on Kroll (2011, 2018):

3 As a robustness analysis, the analyses were conducted with self-employed individuals too. Here, the control variable for employment duration was omitted because it was not available for self-employed individuals. This leads to very similar results (cf. Table A1 in the appendix). Comparable results can also be observed when the models are carried out stratified by gender as well as full-time/part-time or if employees under age 25 are excluded.

4 See Kroll (2011) for detailed documentation of this approach based on the BIBB/BAuA Employment Survey 2006. The scales were updated and adapted based on the BIBB/BAuA Employment Survey 2012, for which the Stata do-file has been made available online (see Kroll 2015, 2018).

1. The individual items are dichotomised (frequently vs. sometimes, rarely, never or never vs. frequently, sometimes, rarely; see Table 1) and added up to individual total scores for the six categories.[5] In doing so, people with missing information are excluded. Since the number of included items varies between categories, the sum scores/scales are z-standardised.
2. The occupational group-specific index values are calculated using multi-level models, which take the hierarchical structure of occupational classifications (ISCO 2008, KldB 1992) into account by including three different levels and various control variables. The six standardised sum scores are thus used as dependent variables for the random intercept model (see Kroll 2011, p. 72).
3. The values predicted on the basis of the multi-level models are saved for the different levels (2, 3, 4-digit groups) of the occupational classifications (ISCO 2008, KldB 1992). They are thereby selected in a way that takes the variation of the respective job demand or resource between occupations into account but not the variation resulting from the included individual characteristics (cf. Kroll 2011, p. 73). The different levels of the occupational classifications are calculated in such a way that the adjacent higher-aggregated level is taken as the base value (starting with the 2-digit code) and the random effects of every respective level are added. This "top-down" way of calculating aims to take into account that the classification's lower-level values will tend to be estimated less precisely due to the lower number of cases per group.

Finally, these values are divided into 10 groups (deciles), which each represent the level of occupational exposure, based on their distribution. The values thus vary between 1 (belonging to the 10 % of occupations with the lowest job demands) and 10 (belonging to the 10 % of occupations with the highest job demands).

3.1 Item selection and grouping into six scales

Based on theoretical considerations (in particular the Job Demands-Resources model), the categories were formed, and the items assigned to them. Additionally, these assignments were tested empirically using a variety of methods (factor analysis, Cronbach's alpha). Table 1 shows the way the selected items were assigned to the six dimensions. Job demands were coded with 1 if they occurred frequently, and with 0 if they did not occur frequently. Two items on social support (F700_08, F700_09) are the exception. They were inversely coded so as to be interpreted as resources in accordance with the other items in that category. Table 1 also shows the mean and the standard deviation (SD) on the generated (unstandardised) sum scores. The Cronbach's alpha values give an indication of the internal consistency of the respective scales and vary within the acceptable range between 0.53 (Scale: autonomy) and 0.76 (Scale: physical demands).[6]

5 A special feature of the BIBB/BAuA Employment Survey is that people who are frequently confronted with a particular job demand are subsequently asked whether they perceive this demand as stressful or not. In contrast to Kroll (2018), the stress-related questions are not considered in the publication at hand. Instead, the procedure is based on Kroll (2011) who argues that this strong criterion should only consider strains that are characteristic of the workplace. The questions specifically relating to stress are not considered in the JEM at hand, because, among other things, this would make weighting impossible for three out of six categories due to the selected variables and coding (e. g., autonomy) without making further assumptions.

6 There are various threshold values in the literature for good or acceptable Cronbach's alpha values, namely, between 0.7 and 0.8. Based on these thresholds, especially the "autonomy" category, at 0.53, would be in the unacceptable range. The comparatively low value may be explained by the fact that there were merely three items available in the "autonomy" category and the value level of Cronbach's alpha is influenced by the amount of included items. Moreover, the selected categories should be understood more in terms of formative constructs, in which the items overall do not correlate as highly as they do in reflective constructs (i. e., they reflect various indicators of a latent construct) and a low Cronbach's alpha value is thus not an indication of non-existent validity (see Christophersen and Grape 2007). The categories were thus selected with a particular focus on their significance for constructing a JEM that is as comprehensive as possible, which is why the construct is not omitted despite the low Cronbach's alpha value (see, e. g., Schmitt 1996 for a critical discussion of the alpha coefficient).

Tab. 1 Included items on working conditions and sample statistics

	Item	Cronbach's alpha	Mean value	SD	N
Physical demands (5 items)		0.761	1.676	1.042	17,539
Frequently: Working in a standing position	F600_01				
Frequently: Working in a sitting position for at least one hour without interruption	F600_02				
Frequently: Performing work requiring great manual dexterity	F600_07a				
Frequently: Lifting and carrying heavy loads	F600_03				
Frequently: Working in forced positions	F600_07b				
Environmental demands (5 items)		0.673	0.656	1.093	17,561
Frequently: Working in smoky or dusty conditions or under gases and vapours	F600_04				
Frequently: Working in conditions of cold, heat, wet, moisture or draughts	F600_05				
Frequently: Working with oil, fat, dirt and filth	F600_06				
Frequently: Working in bright or insufficient lighting	F600_09				
Frequently: Working in noisy conditions	F600_12				
Work intensity (6 items)		0.668	2.420	1.687	17,533
Overchallenged by workload	F410				
Frequently: Deadline/performance pressure	F411_01				
Frequently: Being disturbed/interrupted at work	F411_06				
Frequently: Performing different tasks or processes at the same time	F411_09				
Frequently: Go to the limits of one's capabilities	F411_12				
Frequently: Having to work very quickly	F411_13				
Autonomy (3 items)		0.530	1.676	0.999	17,487
Frequently: Ability to plan and organise own work	F700_02				
Frequently: Ability to influence the amount of work	F700_03				
Frequently: Ability to decide when to take a break	F700_06				
Social support (7 items)		0.635	3.728	1.579	16,913
Frequently: Feel part of a community	F700_10				
Frequently: Good collaborations	F700_11				
Frequently: Support from colleagues	F700_12				
Frequently: Support from direct supervisor	F700_13				
Frequently: Praise/recognition from direct supervisor	F700_14				
Never: Not being informed in time about far-reaching decisions	F700_08				
Never: Not receiving necessary information about the job in time	F700_09				
Working time location (3 items)		0.729	0.762	1.038	17,541
Work on Saturdays (at least once a month)	F220				
Work on Sundays (at least once a month)	F223				
Working time beyond 07:00-19:00	F209				
Control variables					
Female	zpsex	-	0.510	0.500	17,608
Age (years)	zpalter	-	46.6	11.1	17,608
Working time (hours per week)	t_waz	-	38.0	10.7	17,608
Tenure, current job (years)	F511_j	-	10.5	9.5	17,121

Note: Results refer to dependent employees; source: BIBB/BAuA Employment Survey 2018, unweighted results.

3.2 Calculation of JEMs using multi-level models

To determine the average job exposure of the various occupational groups, the next step consists of calculating linear multi-level models (random intercept), in which the six formed scales are included as dependent variables. The different levels of hierarchy of the occupational classifications (2, 3, 4-digit groups) function as the different levels of the model. In addition, we control for differences in job demands by age (z-standardised), sex, working time (ln), and job tenure (ln). Table 2 shows the results of the multi-level models for the occupational classifications ISCO 2008 and KldB 1992.

It can be seen that, with a few exceptions, the included control variables are significantly associated with the respective job demands. Job demands seem to decrease with age regardless of occupation, whereas the degree of autonomy tends to increase. Women tend to report significantly higher work intensity and fewer unfavourable aspects of working time location but also less autonomy in the workplace. Job demands seem to increase with increasing weekly working hours and experience in the respective job.

The extent to which the different job demands vary between different occupations can be estimated based on intraclass correlations. They indicate the share of variance in the respective job demands that is attributable to different occupational levels (2, 3, 4-digit groups). Intraclass correlation varies between 0, if an occupational level does not yield any information, and 1, if all members of an occupational group are identical. Generally, intraclass correlation is highest for the first and coarsest level (2-digit groups), while the increment that is attributable to the two lower levels of the hierarchy (3, 4-digit groups) is comparatively low. The ISCO model for the working time location is an exception as all levels contribute roughly the same amounts, the lowest level even slightly more than the coarsest. Taken together, the high intraclass correlations indicate that the considered job demands vary greatly between occupations. This is especially true for physical job demands, where 55.4 % (ISCO 2008) or 57.6 % (KldB 1992) of the variance can be attributed to the different occupational levels (Table 2, ICC: total; the sum of the intraclass correlation across all three levels of hierarchy). Thus, the variation that can be attributed to occupational levels is even greater than the residual variation, i.e. the variation that can be attributed to the individual level. Environmental job demands (42.9 % and 52.0 %, respectively) as well as the working time location (40.2 % and 41.7 %, respectively) vary between occupations to a large extent. Values for autonomy in the workplace (23.8 % and 24.3 %, respectively) are slightly lower. Differences in work intensity (6.1 % or 5.5 %, respectively) and particularly in social support (≤ 1.0 % in each case) can be attributed to occupational levels to a much lesser extent. It stands to reason that work intensity and the degree of social support in different occupations are more strongly affected by other (individual, organisational or firm-specific) characteristics than by the occupation-specific level. This is in line with observations from previous studies developing JEMs for psycho-social factors that also had low validity, especially for social support (e.g., Nübling et al. 2017, Niedhammer et al. 2018, Hanvold et al. 2018). Since only a maximum of 1 % of the variation in the social support construct can be attributed to differences between occupations, the added value for the occupational group-specific JEM presented here is very low. For this reason, the “social support” category is not considered further and is also not included in the JEM. Occupation-specific differences in work intensity are slightly greater but still relatively small. However, this construct is included in the JEM because it has to be regarded as an important job demand in today’s world of work. When applying the JEM in analyses/interpretations, it should be noted, however, that work intensity hardly differentiates between occupations. Overall, the adjustment of the models for the KldB 1992 classification is slightly better than for the ISCO 2008 classification (Table 2, ICC: total).

Tab. 2 Results of the multi-level model (random intercept) with demand scales (cf. Table 1) as dependent variable

	ISCO 2008						KldB 1992					
	Physical	Environmental	Work intensity	Autonomy	Social support	Working time location	Physical	Environmental	Work intensity	Autonomy	Social support	Working time location
Male	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Female	0.0361*** (0.009)	0.0018 (0.010)	0.1284*** (0.011)	–0.0641*** (0.012)	0.0049 (0.010)	–0.0546*** (0.012)	0.0196*** (0.009)	–0.0034*** (0.010)	0.1310*** (0.011)	0.0625*** (0.012)	0.0007*** (0.010)	0.0486*** (0.012)
Age (z-standardised)	–0.0301*** (0.004)	–0.0437*** (0.005)	–0.0136*** (0.005)	0.0238*** (0.006)	-0.0033 (0.005)	–0.0337*** (0.006)	–0.0318*** (0.004)	–0.0442*** (0.005)	–0.0110* (0.005)	0.0270*** (0.006)	–0.0027 (0.005)	–0.0367*** (0.006)
ln (working time in hours)	0.0447*** (0.012)	0.1335*** (0.014)	0.4252*** (0.015)	0.0640*** (0.016)	–0.1859*** (0.014)	0.2768*** (0.016)	0.0391*** (0.012)	0.1270*** (0.013)	0.4328*** (0.014)	0.0842*** (0.016)	0.1849*** (0.014)	0.2648*** (0.015)
ln (years in current job)	0.0253*** (0.004)	0.0331*** (0.005)	0.0443*** (0.005)	0.0026 (0.005)	–0.0371*** (0.005)	0.0327*** (0.005)	0.0266*** (0.004)	0.0312*** (0.004)	0.0435*** (0.005)	0.0038 (0.005)	0.0384*** (0.005)	0.0328*** (0.005)
Intraclass correlations (ICC)												
ICC: 2-digit groups	0.422	0.330	0.022	0.138	0.000	0.127	0.370	0.421	0.020	0.122	0.002	0.197
ICC: 3-digit groups	0.016	0.048	0.025	0.045	0.003	0.131	0.109	0.037	0.016	0.059	0.006	0.140
ICC: 4-digit groups	0.117	0.051	0.014	0.054	0.006	0.144	0.097	0.062	0.020	0.062	0.002	0.080
ICC: total	0.554	0.429	0.061	0.238	0.009	0.402	0.576	0.520	0.055	0.243	0.010	0.417
Chi^2	12478	5731	682	3358	31	7308	12979	6068	654	3143	53	7822
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LL0	–18425	–17068	–15881	–18463	–13714	–20165	–18441	–17073	–15900	–18484	–13738	–20189
LL1	–12087	–13921	–14948	–16685	–13534	–16428	–11852	–13758	–14977	–16815	–13545	–16193
Pseudo-R^2	0.344	0.184	0.059	0.096	0.013	0.185	0.357	0.194	0.0580	0.090	0.0140	0.198
N	17,081	17,099	17,075	17,034	16,427	17,080	17,105	17,123	17,099	17,057	16,450	17,104

Note: * p<0.05, ** p<0.01, ***p<0.001; ICC: Intraclass correlation for each level of differentiation of the occupational classification; Chi^2: Chi^2 test model with vs. model without random intercepts; P: P-value of the Chi^2 test; LL0: Log-likelihood of the zero model only with constant, without random intercepts; LL1: Log-likelihood of the full model; Pseudo-R^2 according to MacFadden: 1-(LL1/ LL0); source: BIBB/BAuA Employment Survey 2018, unweighted results.

3.3 Aggregation and export of occupational group-specific JEM[7]

The final step consists of predicting the job demand indices based on the multi-level models (cf. Chapter 3.2 and Table 2) while taking into account the occupation-specific effects, standardising them (average=0, standard deviation=1), and aggregating them across the respective levels (2, 3, 4-digit groups) of the occupational classifications. Table 3 summarises the share of occupations at each occupational classification's level of hierarchy for which a value could be assigned to the job exposure indices. The coverage of occupations, and thus also of the indices, decreases as the degree of differentiation of occupational classifications within the BIBB/BAuA Employment Survey increases (see also Kroll 2011, p. 77). While using the 2-digit groups can still cover a majority of the occupational main groups (ISCO 2008: 95.3 %, KldB 1992: 97.7 %), coverage is much lower, particularly for the 4-digit groups of the KldB 1992 (ISCO 2008: 86.5 %, KldB 1992: 51.2 %).

Tab. 3 Coverage of occupational groups by classification

	ISCO 2008			KldB 1992		
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
Number of groups	43	130	436	88	369	2287
Covered by BIBB/BAuA 2018	42	123	391	87	353	1275
Covered by indices[A]	41	119	380	87	346	1187[B]
Covered by indices in %[A]	95.3	91.5	87.2	98.9	93.8	51.9
Average observations per group[A]	454.0	157.4	49.8	221.9	55.3	15.4

Note: [A] Values vary slightly depending on the index under consideration; [B] 1180 with complete data. Source: BIBB/BAuA Employment Survey 2018; cf. Kroll (2011), Table 6, p. 77

Table 4 shows the calculated JEM for the ISCO 2008 2-digit groups as an example. The values can be interpreted as follows: lower values indicate lower demands or resources in the respective occupational group, while higher values indicate higher demands. Overall, the results are as expected. It is shown that particularly manual occupations (e.g., labourers in construction and finishing specialists, metalworkers, elementary occupations, assembly occupations but also cleaning workers) are among the top 10 % of occupations in terms of physical and environmental job demands and are thus characterised by high physical and environmental exposure. Compared to this, physical and environmental exposure is lowest in academic and office-based jobs (e.g., occupations in business administration and management). Work intensity is particularly pronounced among associate professionals in healthcare and managers in various areas. Academic professionals, such as scientists and managers in various areas, in particular, have an above-average amount of job autonomy. In contrast, job autonomy is particularly low in manual occupations, which include drivers and mobile plant operators, metal workers, unskilled workers, and assemblers. Above-average demands in terms of the working time location are found among occupations in the area of personal services, security and protective services as well as drivers and mobile plant operators or sales workers, among others.

The full representation of the JEM for all levels of the individual occupational classifications is made available as separate files in an Excel, SPSS and Stata format.[8]

7 Kroll (2011, 2018) puts out/aggregates the job exposure indices in deciles (weighted), i.e., 10 groups are differentiated in each category with the aim of minimising possible bias (including measurement errors).

8 They are made available by FDZ-BAuA: *www.baua.de/fdz*

In order to be able to use the values of the JEM for subsequent analyses with other data, they have to be merged with the dataset in question using the variable of the respective occupational classification. Overall, the values of the JEM for the different occupational classifications are plausible across the various levels, so that the value of a 2-digit group, for example, is usually within the range of the values of the 3-digit groups. Due to the specific construction of the JEM (cf. Chapter 3), which, among other things, does not take into account the number of cases per group[9], deviations may occur in some cases. For example, the values of the lower levels tend to be estimated more imprecisely due to the lower number of cases per group. Dragano (2007, p. 142) and Bödeker (2002) therefore recommend using the values of the respective higher occupational levels for cells with case numbers of less than 10. For example, if the cell size of the 4-digit group 1234 is smaller than 10, the value of the corresponding 3-digit group 123 would be used for this 4-digit group. However, to make the JEM available for as many occupations as possible, no adjustment is conducted in the current calculation of the JEM. To reduce the described deviations, the values are displayed using the distribution in deciles instead of individual values.

Tab. 4 Exemplary excerpt from the JEM: Working conditions according to ISCO 2008 2-digit groups

Code	ISCO 2008 2-digit groups	Physical	Environmental	Work intensity	Autonomy	Working time location
1	Commissioned armed forces officers	5	4	5	4	5
2	Non-commissioned armed forces officers	9	10	4	3	6
2	Armed forces occupations, other ranks	7	8	3	3	6
11	Chief executives, senior officials and legislators	3	3	9	9	6
12	Administrative and commercial managers	1	1	9	10	3
13	Production and specialized services managers	4	4	10	9	3
14	Hospitality, retail and other services managers	5	6	9	9	9
21	Science and engineering professionals	3	1	5	10	1
22	Health professionals	7	6	9	3	8
23	Teaching professionals	6	5	3	4	5
24	Business and administration professionals	1	1	7	9	2
25	Information and communications technology professionals	1	1	3	9	3
26	Legal, social and cultural professionals	3	4	5	7	6
31	Science and engineering associate professionals	5	8	3	6	7
32	Health associate professionals	8	6	10	2	8
33	Business and administration associate professionals	1	2	8	7	1
34	Legal, social, cultural and related associate professionals	8	7	6	5	9
35	Information and communications technicians	5	6	5	7	5
41	General and keyboard clerks	4	3	2	6	4
42	Customer service clerks	4	5	4	3	6

9 It must also be taken into account that the BIBB/BAuA Employment Survey is not representative, in particular, for the lower levels of occupational classifications. Inclusion or weighting based on the size of a group is therefore not advisable.

Tab. 4 Exemplary excerpt from the JEM: Working conditions according to ISCO 2008 2-digit groups

Code	ISCO 2008 2-digit groups	Physical	Environ-mental	Work intensity	Autonomy	Working time location
43	Numerical and material recording clerks	5	4	6	7	4
44	Other clerical support workers	6	6	6	4	5
51	Personal services workers	9	9	7	4	10
52	Sales workers	7	7	7	3	9
53	Personal care workers	9	7	6	2	8
54	Protective services workers	7	9	2	2	10
61	Market-oriented skilled agricultural workers	10	10	1	4	9
62	Market-oriented skilled forestry, fishery and hunting workers	10	10	2	3	*6*
71	Building and related trades workers (excluding electricians)	10	10	1	3	3
72	Metal, machinery and related trades workers	10	10	1	1	7
73	Handicraft and printing workers	7	9	2	3	6
74	Electrical and electronic trades workers	9	8	1	5	4
75	Food processing, woodworking, garment and other craft and related trade workers	9	9	1	1	6
81	Stationary plant and machine operators	9	10	2	1	9
82	Assemblers	10	9	2	1	6
83	Drivers and mobile plant operators	6	9	1	1	10
91	Cleaners and helpers	10	10	4	5	7
92	Agricultural, forestry and fishery labourers	10	10	2	2	6
93	Labourers in mining, construction, manufacturing and transport	10	9	2	1	7
94	Food preparation assistants	10	9	5	1	9
96	Refuse workers and other elementary workers	10	10	1	3	8

Note: 1: least exposure 10 %, 10: highest exposure 10%; source: BIBB/BAuA Employment Survey 2018, unweighted results.

4 Replication based on the BAuA-Working Time Survey 2015

As discussed above, it is difficult to evaluate the quality of a JEM as there is no gold standard for their calculation. Rather, its quality or performance depends on its specific application (cf. Peters 2020). In order to be able to make claims about the validity of the calculated JEM, the following section aims at replicating the results of the JEM for the ISCO 2008 classification in the best possible way. This is done based on the BAuA-Working Time Survey 2015. The BAuA-Working Time Survey is particularly suitable because it is in many respects similar to the BIBB/BAuA Employment Survey. While the thematic focus of this extensive survey is on various aspects of the realities of working time in Germany, it also gathers data on psycho-social job demands, resources, and also some physical working conditions. The two surveys are also comparable with regard to the population of the sample – employees aged 15 and over with at least 10 hours of paid work per week (for details, see Häring et al. 2016).

A considerable advantage here is that the formulation of the questions of many items was based on the BIBB/BAuA Employment Survey, making them directly comparable. Table A2 in the appendix shows the comparability of the two surveys with regard to the items included in the JEM. It is shown that particularly the autonomy and working time location categories are comprehensively covered by the BAuA-Working Time Survey. Regarding the work intensity category, 5 of the 6 items and 3 out of 5 items in terms of physical and environmental working conditions are also available in the BAuA-Working Time Survey. At 4 out of 7 items, the selected items in the social support category are not covered quite as well. The Cronbach's alpha values for the individual categories are consistently lower in the BAuA-Working Time Survey but on a comparable scale. Despite the reduced coverage of the various categories, the results of the multi-level model are basically very similar to the results based on the BIBB/BAuA Employment Survey. Table A3 depicts the results of the multi-level models for the ISCO 2008 classification based on the BAuA-Working Time Survey.

Overall, the associations between the included control variables and the different job demand indices are comparable, although the size of the estimators deviates somewhat from the main results (cf. Table 2). Similar to the results based on the BIBB/BAuA Employment Survey 2018, the overall intraclass correlations indicate that the considered working conditions differ considerably between occupations. Generally, the variation in the different categories, which can be attributed to occupation, is slightly lower than in the BIBB/BAuA Employment Survey 2018, which may be due, in part, to the reduced number of items (see ICC: total). The adjustment in the BAuA-Working Time Survey 2015 is slightly better only for autonomy and social support. Finally, if one compares the predicted values of the JEM (deciles) of both surveys, the overall results are also very similar, with only slight discrepancies (cf. Table A4 in the appendix). Exceptions include the work intensity and autonomy categories, where the discrepancies are sometimes more pronounced. In summary, however, the results based on the BAuA-Working Time Survey point towards the validity of the presented JEM.

5 Discussion and conclusion

The publication at hand documents the development of a job-exposure matrix based on the data of the BIBB/BAuA Employment Survey 2018, assigning each occupation with up-to-date levels of exposure for different job demands. Overall, the analyses conducted so far indicate that the calculated exposure values are plausible. It has been shown that the validity of the models (and thus the calculated JEMs) is good for physical, environmental, and working time-related job demands. The models provide a more moderate adjustment for autonomy and a rather poor adjustment for work intensity. This result is in line with various other studies on psycho-social JEMs, where the results for autonomy or monotony are generally still the best, while the adjustment for characteristics that can be attributed to the construct of social support or leadership is consistently the worst (e.g., Niedhammer et al. 2018, Hanvold et al. 2019, Nübling et al. 2017). These constructs appear to be more strongly impacted by other (individual, organisational or firm-specific) features, which is why exposure assessment based on occupations alone appears insufficient, making these constructs overall less suitable for JEMs (Peters 2020, Nübling et al. 2017). This should be taken into account when using JEM or interpreting the results in the future. Moreover, it should be noted that, as the levels of hierarchy become more fine-grained, the values tend to become less precise – despite opting for an empirical approach that yields more robust estimators for rare occupations.

There are also differences in adjustment depending on the considered occupational classification, with better adjustment for the KldB 1992. The (external) validity of the calculated JEMs should therefore be tested in greater depth in the future, particularly by way of application.

Validity, or "performance", of the JEM always depends on its specific application as well as the exposures and outcomes that are being considered (Peters 2020). It is therefore recommended to conduct analyses on various BAuA-related research questions using the JEMs within the BIBB/BAuA Employment Survey 2018 as well as with external datasets (e.g., BAuA-Working Time Survey, European Working Conditions Surveys, pension and health insurance data).[10]

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10 The authors would be pleased to receive feedback on any difficulties using the JEM, e.g., with external data, certain research questions, or regarding certain occupational classifications.

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Appendix

Tab. A1 Robustness analysis: Multi-level model (random intercept) with demand scales (cf. Table 1) as dependent variable, without controlling for tenure

	ISCO 2008						KldB 1992					
	Physical	Environmental	Work intensity	Autonomy	Social support	Working time location	Physical	Environmental	Work intensity	Autonomy	Social support	Working time location
Male	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Female	0.0366*** (0.009)	0.0006 (0.010)	0.1261*** (0.010)	–0.0672*** (0.012)	0.0037 (0.010)	–0.0690*** (0.012)	0.0195* (0.009)	–0.0053 (0.010)	0.1286*** (0.010)	–0.0647*** (0.012)	0.0007*** (0.010)	–0.0649*** (0.012)
Age (z standardized)	–0.0165*** (0.004)	–0.0289*** (0.004)	0.0033 (0.004)	0.0328*** (0.005)	–0.0219*** (0.004)	–0.004 (0.005)	–0.0168*** (0.004)	–0.0298*** (0.004)	0.0048 (0.004)	0.0372*** (0.005)	–0.0219*** (0.004)	–0.0078 (0.005)
ln (working time in hours)	0.0492*** (0.011)	0.1219*** (0.012)	0.4259*** (0.013)	0.0775*** (0.015)	–0.1858*** (0.014)	0.2968*** (0.015)	0.0394*** (0.011)	0.1175*** (0.012)	0.4326*** (0.013)	0.1016*** (0.015)	–0.1852*** (0.014)	0.2894*** (0.014)
Intraclass correlations (ICC)												
ICC: 2-digit groups	0.408	0.316	0.012	0.154	0.000	0.120	0.368	0.389	0.016	0.124	0.002	0.181
ICC: 3-digit groups	0.019	0.048	0.027	0.037	0.004	0.119	0.106	0.047	0.02	0.067	0.006	0.110
ICC: 4-digit groups	0.117	0.055	0.017	0.061	0.006	0.127	0.098	0.065	0.021	0.065	0.003	0.083
ICC: total	0.544	0.419	0.056	0.251	0.011	0.366	0.572	0.502	0.056	0.255	0.010	0.373
Chi²	13993	6516	769	3808	40	7193	14761	6913	770	3530	55	7786
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LL0	–20967	–19509	–17910	–20171	–14332	–23192	–20987	–19526	–17931	–20196	–14357	–23222
LL1	–13926	–15989	–16864	–18130	–14182	–19470	–13563	–15808	–16880	–18295	–14198	–19202
Pseudo-R^2	0.336	0.180	0.058	0.101	0.010	0.160	0.354	0.190	0.059	0.094	0.011	0.173
N	19,407	19,429	19,306	18,431	17,169	19,400	19,435	19,457	19,333	18,457	17,194	19,428

Note: * p<0.05, ** p<0.01, ***p<0.001; ICC: Intraclass correlation for each level of differentiation of the occupational classification; Chi²: Chi²-test model with vs. model without random intercepts; P: p-value of the Chi² test; LL0: Log-likelihood of the zero model only with constant, without random intercepts; LL1: Log-likelihood of the full model; Pseudo-R^2 according to MacFadden: 1-(LL1/ LL0); source: BIBB/BAuA Employment Survey 2018, unweighted results.

Tab. A2 Comparison of included items, BIBB/BAuA 2018 and BAuA-WTS 2015

		BIBB/BAuA 2018		BAuA-WTS 2015	
		Variable	Cronbach's alpha	Variable	Cronbach's alpha
Physical	Frequently: Working in a standing position	F600_01	0.7532	A500_1	0.6778
	Frequently: Working in a sitting position for at least one hour without interruption	F600_02			
	Frequently: Performing work requiring great manual dexterity	F600_07a			
	Frequently: Lifting and carrying heavy loads	F600_03		A500_2	
	Frequently: Working in forced positions	F600_07b		A500_4	
Environmental	Frequently: Working in smoky or dusty conditions or under gases and vapours	F600_04	0.6725		0.5797
	Frequently: Working in conditions of cold, heat, wet, moisture or draughts	F600_05		A500_3	
	Frequently: Working with oil, fat, dirt and filth	F600_06			
	Frequently: Working in bright or insufficient lighting	F600_09		A500_5	
	Frequently: Working in noisy conditions	F600_12		A500_6	
Work intensity	Overchallenged by workload	F410	0.6619	A502	0.5982
	Frequently: Deadline/performance pressure	F411_01		A400_3	
	Frequently: Being disturbed/interrupted at work	F411_06		A404_6	
	Frequently: Performing different tasks or processes at the same time	F411_09		A404_5	
	Frequently: Go to the limits of one's capabilities	F411_12			
	Frequently: Having to work very quickly	F411_13		A402	
Autonomy	Frequently: Ability to plan and organise own work	F700_02	0.5411	A415_2	0.5093
	Frequently: Ability to influence the amount of work	F700_03		A415_3	
	Frequently: inability to decide when to take a break	F700_06		A415_4	
Social support	Frequently: Feel part of community	F700_10	0.6306	A416_1	6494
	Frequently: Good collaborations	F700_11		A416_2	
	Frequently: Support from colleagues	F700_12		A416_3	
	Frequently: Support from direct supervisor	F700_13		A416_4	
	Frequently: Praise/recognition from direct supervisor	F700_14			
	Never: Not being informed in time about far-reaching decisions	F700_08			
	Never: Not receiving necessary information about the job in time	F700_09			
Working time	Work on Saturdays (at least once a month)	F220	0.7215	A230/ A231	0.6490
	Work on Sundays (at least once a month)	F223		A232/A233	
	Working time beyond 07:00-19:00	F209		A217	

Note: Results relate to dependent employees; source: BIBB/BAuA Employment Survey 2018, BAuA-Working Time Survey 2015, unweighted results.

Tab. A3 Replication of multi-level models (random intercept) based on the BAuA-Working Time Survey 2015

	ISCO 2008					
	Physical	Environ-mental	Work intensity	Autonomy	Social support	Working time location
Male	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Female	0.0328** (0.011)	0.0301* (0.012)	0.1264*** (0.011)	–0.1162*** (0.012)	–0.0117 (0.013)	–0.0642*** (0.012)
Age (z-standardized)	–0.0341*** (0.005)	–0.0252*** (0.006)	–0.0174*** (0.005)	0.0152** (0.006)	–0.0202*** (0.006)	–0.0208*** (0.006)
ln (working time in hours)	0.1414*** (0.013)	0.1886*** (0.015)	0.4289*** (0.014)	0.0948*** (0.015)	–0.1618*** (0.017)	0.3490*** (0.016)
ln (years in current job)	0.0100* (0.004)	0.0157** (0.005)	0.0380*** (0.005)	0.0197*** (0.005)	0.0076 (0.005)	0.0047 (0.005)
Intraclass correlations (ICC)						
ICC: 2-digit groups	0.337	0.222	0.015	0.148	0.015	0.097
ICC: 3-digit groups	0.042	0.052	0.011	0.031	0.004	0.151
ICC: 4-digit groups	0.114	0.079	0.024	0.072	0.009	0.105
ICC: total	0.493	0.352	0.050	0.252	0.029	0.354
Chi²	11952	5145	597	3521	138	6298
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LL0	–21429	–20251	–17011	–19355	–15926	–19569
LL1	–15408	–17551	–16065	–17367	–15819	–16247
Pseudo-R²	0.2810	0.1330	0.0560	0.1030	0.0070	0.1700
N	18,215	18,191	18,180	17,982	15,967	16,878

Note: * p<0.05, ** p<0.01, ***p<0.001; ICC: Intraclass correlation for each level of differentiation of the occupational classification; Chi²: Chi²-test model with vs. model without random intercepts; P: p-value of the Chi² test; LL0: Log-likelihood of the zero model only with constant, without random intercepts; LL1: Log-likelihood of the full model; Pseudo-R² according to MacFadden: 1-(LL1/ LL0); source: BAuA-Working Time Survey 2015, unweighted results.

Tab. A4 Deviation of JEM (deciles) BIBB/BAuA Employment Survey 2018 and BAuA-WTS 2015

Code	ISCO 2008 2-digit groups	Physical	Environ-mental	Work intensity	Autonomy	Working time location
1	Commissioned armed forces officers	not available in BAuA-WTS				
2	Non-commissioned armed forces officers	not available in BAuA-WTS				
2	Armed forces occupations, other ranks	not available in BAuA-WTS				
11	Chief executives, senior officials and legislators	0	2	1	–1	1
12	Administrative and commercial managers	0	0	–1	0	–1
13	Production and specialized services managers	0	0	0	0	–1
14	Hospitality, retail and other services managers	0	1	–1	1	0
21	Science and engineering professionals	1	–2	–1	1	–1
22	Health professionals	1	2	4	–3	1
23	Teaching professionals	0	–1	1	0	0
24	Business and administration professionals	0	0	–3	–1	0
25	Information and communications technology professionals	0	0	–2	1	0
26	Legal, social and cultural professionals	0	1	2	–2	–1

Tab. A4 Deviation of JEM (deciles) BIBB/BAuA Employment Survey 2018 and BAuA-WTS 2015

Code	ISCO 2008 2-digit groups	Physical	Environ-mental	Work intensity	Autonomy	Working time location
31	Science and engineering associate professionals	0	0	–1	0	0
32	Health associate professionals	1	1	2	–1	0
33	Business and administration associate professionals	0	0	2	0	0
34	Legal, social, cultural and related associate professionals	0	0	3	–2	0
35	Information and communications technicians	0	0	0	1	0
41	General and keyboard clerks	1	–1	–2	–1	0
42	Customer service clerks	0	0	–5	1	–1
43	Numerical and material recording clerks	1	0	–2	4	1
44	Other clerical support workers	1	1	1	–2	1
51	Personal services workers	1	1	3	–1	0
52	Sales workers	0	0	–2	–1	0
53	Personal care workers	–1	–1	–1	0	–1
54	Protective services workers	0	0	0	1	0
61	Market-oriented skilled agricultural workers	0	1	0	–3	0
62	Market-oriented skilled forestry, fishery and hunting workers	0	0	1	–3	–1
71	Building and related trades workers (excluding electricians)	0	0	0	1	0
72	Metal, machinery and related trades workers	1	1	–2	0	1
73	Handicraft and printing workers	–1	1	–4	1	–1
74	Electrical and electronic trades workers	0	–1	0	3	0
75	Food processing, woodworking, garment and other craft and related trade workers	0	0	–4	–1	0
81	Stationary plant and machine operators	0	0	–1	0	–1
82	Assemblers	2	1	–2	0	0
83	Drivers and mobile plant operators	–1	–1	0	0	0
91	Cleaners and helpers	0	0	3	3	–2
92	Agricultural, forestry and fishery labourers	1	1	–1	–1	0
93	Labourers in mining, construction, manufacturing and transport	0	1	1	0	2
94	Food preparation assistants	1	0	0	0	2
96	Refuse workers and other elementary workers	1	0	0	1	–1

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