Research Paper

Assessing Spatial Impacts of Digitalisation on Labour Markets: Methodological Approaches

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Abstract

Technological advancement is a major factor in shaping the future of work, which in consequence affects labour markets and economic geographies. Although concrete effects of digitalisation are challenging to predict, we can develop proxies based on tasks or skills and how they relate to abilities of humans and/or computers. These proxies consequently can be aggregated on an occupational level to describe the effects of digitalisation of certain jobs and to relate them to labour market statistics to understand implications on various geographic levels.

This paper presents the findings of a case study on the German labour market at the district (Kreise) level and analyses differences in the potential effects of digitalisation across regions. While no clear spatial patterns can be identified, results suggest a polarisation of labour markets both on a national and local levels, as well as deepening divides between urban and rural regions.

The study uses structured regional labour market statistics and two digitalisation indicators from existing research (Felten et al., 2021; Frey and Osborne, 2017) *to categorise employment concentrations into four typologies ("rising stars," "machine terrain," "human terrain," and "collapsing"). Based on the indicators of Potential Risk of Computerisation (PRoC) and Occupational/Geographic Exposure to AI (AIOE/AIGE) this approach provides an understanding of potential regional economic shifts.*

While focused on German data, this framework could be adapted internationally based on standardised labour market statistics. This allows an identification of regions with high concentrations of employments in sectors that are more vulnerable to transformative or destructive effects of technological advancement and digitalisation.

Keywords

Digitalisation, Labour Market, Artificial Intelligence

1 Introduction

1.1 Background

The current rise of deep learning and advanced computational methods, alongside the broad applicability of related tools in our everyday lives, has nourished research interest in the question of how new technologies might shape the ways we work (Deranty and Corbin, 2024; Frey and Osborne, 2024). Though comparisons of current developments with a new industrial revolution are generally regarded as overestimations (Frey and Osborne, 2024; Samaan, 2023), they impact how and where we perform our tasks and generate new ways of interactions with digital technologies.

Rapid advancements in technologies such as Generative Artificial Intelligence may give the impression that human abilities (and by extension, entire occupations) can easily be conducted by machines. In such cases,

digitalisation exercises a destructive effect, as jobs can be easily taken over by computers. However, the relationship between humans and computers is far more complex and goes beyond simple replication or substitution. Changes are more likely to happen on the level of tasks, instead of entire jobs or occupations (Frey and Osborne, 2024; Samaan, 2023), meaning that these effects are more transformative than disruptive in nature.

To attain a general (spatial) overview of the effect of such transformations, we can use digitalisation indicator sets as proxies to describe the extent of both destructive and transformative effects. Consequently, these proxies can be linked with occupational statistics of spatial units (e.g. on a regional level). This enables a better understanding of how technological advancements might affect different regions.

The following paper follows and extends an approach sketched up by Fossen & Sorgner (2019) and combines two indicators on an occupational level:

- the Potential Risk of Computerisation (PRoC), as defined by Frey & Osborne (2017), measuring the susceptibility of occupations being replaced through computerisation, describing the destructive
- and the Artificial Intelligence Occupational/Geographic Exposure (AIOE/AIGE), as defined by Felten et al. (2021), describing the transformative effects of digitalisation.

The two indicators are linked to labour market statistics of the German labour market on the national, as well as on the regional level within the countries 400 districts (“Kreise”). This enables an understanding of the regional variation of potential effects of digitalisation trends in the labour market.

1.2 Methods in assessing the effects of digitalisation

Though it is unlikely to predict the concrete effects of digitalisation on specific jobs (or the labour market as a whole), research based on occupational profiles can describe potential development paths and tendencies. Previous research has developed indicators of digitalisation based on either the tasks that are linked to occupations (Autor and Handel, 2013; Felten et al., 2021, 2018; Fernández-Macías and Bisello, 2022; Frey and Osborne, 2017), or on the skills that are needed need to perform these tasks (Barbieri et al., 2020; Colombo et al., 2019; Nedelkoska and Quintini, 2018).

An advantage of task- or skill-based approaches is their compatibility with standardised labour market statistics, which classify occupations into hierarchical taxonomies. Apart from providing a simple classification, these taxonomies also link occupations, tasks and skills with each other. This enables the analysis of effects of digitalisation across different geographical areas and/or industries.

The taxonomies are usually defined and maintained by a national or supra-national employment agency, such as the US Department of Labour, which publishes the O*NET/SOC taxonomy[1] as an example. This Taxonomy features 23 major groups (e.g. 17-0000 Architecture and Engineering Occupations) and 93 minor groups (e.g. 17-1010 Architects, Surveyors, and Cartographers), which are then broken down into 459 broad occupations (e.g. Surveyors, Cartographers, and Photogrammetrists) and 867 detailed occupations (e.g. 17-1021 Cartographers and Photogrammetrists). Each of the occupations can have specific skills and tasks assigned to them, which we can match with digitalisation (or other) indicators.

In the presented study, three taxonomies are of relevance:

[1] https://www.onetcenter.org/taxonomy.html

- The O*NET-SOC-taxonomy of the US Department of Labour, which provides the structure for both of the indicator sets (Felten et al., 2021; Frey and Osborne, 2017) used for the analysis
- The KldB-taxonomy[2] of the German Federal Employment Agency, which the available national and regional labour market statistics refer to
- The ISCO-taxonomy of the International Labour Organisation, which corresponds the ESCO-taxonomy[3] of the European Commission, as an intermediate to convert between O*NET-SOC and KldB

1.3 Digitalisation indicators

One of the most widely cited studies in the field of computerisation and labour is the report "Future of Employment" published in 2013 (Frey and Osborne, 2013), with an updated version in 2017 (Frey and Osborne, 2017). It uses a task-based approach to examine how certain computational bottlenecks determine the likelihood of tasks, and consequently of jobs, being automated. The assignment of tasks to occupations is queried from the US Department of Labor's SOC/O*NET database. Based on this, the report presents a classification system that assigns a potential risk of computerisation (referred to as PRoC in this article) to various occupations. These scores range from 0 (unlikely to be automated) to 1 (highly susceptible to automation), and can consequently be interpreted as a measure of the destructive effects of digitalisation (Fossen and Sorgner, 2019).

The report has been influential in urban and regional planning research (Sharifi et al., 2023) and the scores of computerisation (or the methods used to create these) have been projected onto the Austrian (Hat and Stoeglehner, 2020), Irish (Crowley and Doran, 2023) or the US (Frank et al., 2018) context on a (sub-)regional level. These studies point out economic differences in terms of regional vulnerability of labour markets towards computerisation, with especially rural, economically weaker regions being more at risk.

Transfers of "Future of Employment" report onto the German context exist on a national level, using a direct linkage of computerisation potential scores of US-occupations to their German counterparts (Bonin et al., 2015; Brzeski, 2015), or replicating their approach by not transferring occupational but task-level scores (Dengler and Matthes, 2018).

Using a similar approach, we can compare the Electronic Frontier Foundation (EFF) AI Progress Measurement with the 52 skills listed in the SOC/O*NET database. This comparison provides a metric to assess how advances in Artificial Intelligence might impact the labour market, offering a way to compare occupations (Felten et al., 2018). These scores can be considered to describe the transformative effects of digitalisation (Fossen and Sorgner, 2019).

By combining these two metrics, the (transformative) exposure to AI and the (destructive) susceptibility to replacement through automation, it becomes possible to assess the broader impacts of technological progress on the labour market. Fossen and Sorgner (2019) created a two-dimensional matrix combining these indicators to categorise occupations into four quadrants, offering a more structured description of future dynamics of work, as shown in Table 1.

On the X-axis of the matrix we find the scores of computerisation probability from the "Future of Employment" report (Frey and Osborne, 2017). The Y-axis relates to the Advances in AI (Felten et al., 2018)

[2]https://statistik.arbeitsagentur.de/DE/Navigation/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010-Fassung2020/KldB2010-Fassung2020-Nav.html
[3] https://esco.ec.europa.eu/en/classification

metric. The delimitations of the quadrants are based on the median, weighted by the US employment in the occupation groups.

Advances in AI (Felten et al., 2018) / transformative effects of digitalisation	**Q1: Rising Stars** Low destructive, high transformative effects e.g. Physicists (advances in AI-score: 5.91/ computerisation probability score: 0.10)	**Q2: Machine Terrain** High destructive, high transformative effects e.g. Accountants and Auditors (3.70/0.94)
	Q3: Human Terrain Low destructive, low transformative effects e.g. Teacher Assistants (2.54/0.56)	**Q4: Collapsing Occupations** High destructive, low transformative effects e.g. Manicurists and Pedicurists (1.97/0.95)
	Computerisation probability (Frey and Osborne, 2017) / destructive effects of digitalisation	

Table 1: Digitalisation matrix, as used in the reference study (Fossen and Sorgner, 2019)

The strength of this matrix relies in its simplicity and ease of interpretation. Important characteristics of occupations within the quadrants are described as follows (Fossen and Sorgner, 2019):

- **Rising stars occupations** (Q1) require social and creative intelligence, its workers will therefore not be easily replaced through computerisation, however they might need to acquire further skills and qualifications
- **Machine terrain occupations** (Q2) often feature manual skills and while in the short-term necessary qualifications can be obtained to work with new technologies, in the longer term, they might also run into the risk of being easily replaced
- **Human terrain occupations** (Q3) are least affected through digitalisation, minimising the risk of being replaced, however they are also profiting the least from technological advancement in their productivity
- **Collapsing occupations** (Q4) are easily replaced by machines already in the short-term perspective, meaning that workers in this category may need re-qualification

The presented research builds up on the classification according to the matrix described above and relates them to the German national and district-level labour market indicators to understand possible geographic implications of labour market developments.

Besides the application of the scores in a different geographic region, the key difference is the usage of a more recent score for assessing the effects of AI in the labour market: the Artificial Intelligence Occupational (or the derived Geographic) Exposure (AIOE/AIGE) indicator (Felten et al., 2021). This score is a relative metric of occupational scores based on the 52 abilities listed in the O*NET database and the progress of AI scores of the EEF. The scores for each occupational group are calculated by linking them with the importance and prevalence of skills in the respective groups. This enables a more up-to-date and more accurate measurement of possible effects of AI on the labour market.

2 Methods

2.1 Taxonomy classification

The most profound challenge in transferring the two sets of indicators to the German context lies in the conversion between the taxonomies that describe and structure the datasets related to the labour market and employment. There are several ways to match occupations across different taxonomies. One method involves aligning occupations of an external taxonomy with their local counterparts, as seen in the Austrian case study (Hat & Stoeglehner, 2020). A different approach is to use conversion tables, also called "crosswalks" (Bonin et al., 2015). The most accurate results are typically obtained by defining digitalisation scores at the task level and then re-compiling them at the occupational level (Dengler and Matthes, 2018).

For simplicity, the research presented here adopts a crosswalk-based method at the occupational group level. This method allows for the simultaneous comparison of two digitalisation metrics—PRoC and AIOE/AIGE. Moreover, we can assume that scores at the occupational group level are not significantly different from those at the task level when assessed on a relative scale (Nedelkoska and Quintini, 2018), which is the primary focus of this report.

A key limitation of this approach arises from the inherent fuzziness in occupational taxonomies. In many cases, an occupation in one taxonomy may correspond to multiple groups in another. As a result, a single German occupational group may be assigned several different digitalisation scores.

While averages or means of the occupational scores could be used to get one matching score to one occupation group, this tends to obscure extreme values (i.e., very high or low digitalisation scores). To address this, we can use the so-called "uniform distribution" approach, which assigns all potential digitalisation scores to the occupation groups (Bonin et al., 2015). For instance, if a KldB group with 100 workers in one region corresponds to two O*NET-SOC groups with different scores, 50 workers would be assigned to each score.

The hereby presented study follows this approach, taking the transfer of the “Future of Employment” report to Germany (Bonin et al., 2015) as a reference. In this case, we use however a newer and more accurate crosswalk table for ESCO to convert between the US and the European classification, provided by the European Commission (which is responsible for defining and maintaining the ESCO-classification)[4]. The German Federal Employment Agency provides a crosswalk[5] to convert between ESCO/ISCO and their own KldB-taxonomies. Besides the conversion across the three (supra-)national taxonomies, the original codes in the two base studies also needed to be updated, as the crosswalks relate to the newer version of the taxonomy. The Department of Labor provides the necessary conversion tables for this task.

In case of ambiguous matches between taxonomies, both crosswalks provide an estimation of the accuracies of the defined linkages. The SOC/O*NET crosswalk defines matches to be either “exact”, “narrow” (SOC/O*Net group covers more occupations and tasks than the linked ESCO occupational group), ”broad” (as before, just vice-versa) or “close” (with overlaps on both sides). The KldB-crosswalk defines and ranks possible alternatives. For the conversion, the two distinct accuracy metrics of the crosswalks were weighted and added to each other to get a joint weight. For further calculations all matches with the highest available weights were selected.

[4] https://esco.ec.europa.eu/en/about-esco/data-science-and-esco/crosswalk-between-esco-and-onet
[5] https://statistik.arbeitsagentur.de/DE/Statischer-Content/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010-Fassung2020/Arbeitsmittel/Umschluesselungstabellen.html

2.2 Employment data

Employment data for the German labour market was sourced from the Federal Employment Agency (Bundesagentur für Arbeit) and reflects the labour market as of March 2024. This research uses employment data at the 4th level (occupational sub-groups) of the KldB taxonomy on the national level and at the 3rd level (occupational groups) on the regional level to account for different scales of analysis. Based on this, we apply the equal distribution method proposed by Bonin et al. (2015). Occupations at the 4th level of KldB are distributed into the 3rd level based on national figures. These 4th level figures are then distributed evenly into 5th level (pseudo-)classes, where digitalisation indicators are assigned.

It needs to be pointed out that this method does not fully resolve classification issues and assumes the same proportional distribution of occupations across Germany within their respective groups. However, it avoids gravitating towards averages and retains digitalisation values that are located on the extreme ends of the two axes of the indicator matrix. It also facilitates the integration of both AIOE and PRoC indicators, as the same taxonomy conversion applies to both.

2.3 Evaluation

To check the validity of the results of taxonomy conversion, the distribution of scores were compared across taxonomies (Figure 1). The x-axis in both charts show the range of digitalisation scores (PRoC and AIOE) for Germany (orange) and for the US labour market (blue). The utilised uniform distribution approach preservers the shape of both graphs, with many jobs in the PRoC score located at the two extremes, and in the bi-modal distribution in case of AIOE.

Looking at the results of scores in the German labour market, we can see that around 45.60 per cent of the national work force is highly susceptible to automation (working in occupations with scores above 0.7). This number is close to both the estimation of the “Future of Work” report (47%) and the number obtained in Bonin et al. (2015) using the direct translation scores on the occupational level (42%). Deviances in these numbers can be attributed to the different structures of the labour market and the time the labour market statistics refer to.

There is no reference study of the AIOE scores in the German context, nevertheless the numbers of workers with a high AIOE-score (above 1) are comparable when applying the indicator set to the numbers of the US (27.38%) and to the German (26.12%) labour market.

2.4 Technological Approach

The employment data and digitalisation indicators were stored in a PostGIS database, data preparation, analysis and visualisation was performed with help of the libraries Pandas (Pandas development team, 2020), Geopandas (Jordahl et al., 2020) and Matplotlib (Hunter, 2007). Additionally, ChatGPT (OpenAI, 2024) was used for stylistic checking of the presented article.

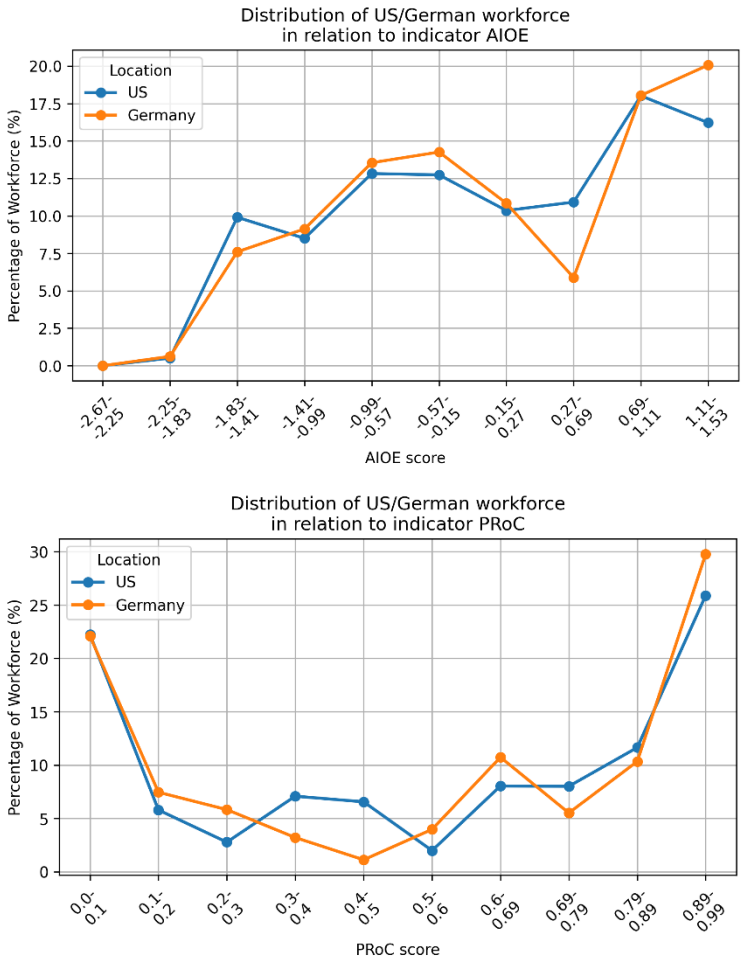


Figure 1: Comparison of the distribution of AIOE and PRoC scores in the German and US labour market (source: own elaboration, 2024)

3 Results

3.1 National level

Figure 2 presents the assignment of occupational groups in the matrix on the German national scale. The size of the bubbles corresponds to the size of the KldB-5-(pseudo)-class, with the two digitalisation indicators assigned to locate them along the x- (PRoC) and y-axis (AIOE). For the definition of the delimitations between the quadrants, we use the weighted medians as done in Fossen & Sorgner (2019), located at 0.66 along the PRoC, and at 0.09 along the AIOE-scale.

Comparing the results to the outcomes of the original study, we see a less narrow distribution of scores along the y-axis, while the AIOE scores used in the presented research seem to be more broadly scattered. This can be attributed to the differences in distributions between the original (Felten et al., 2018) and updated (Felten et al., 2021) AI-related scores.

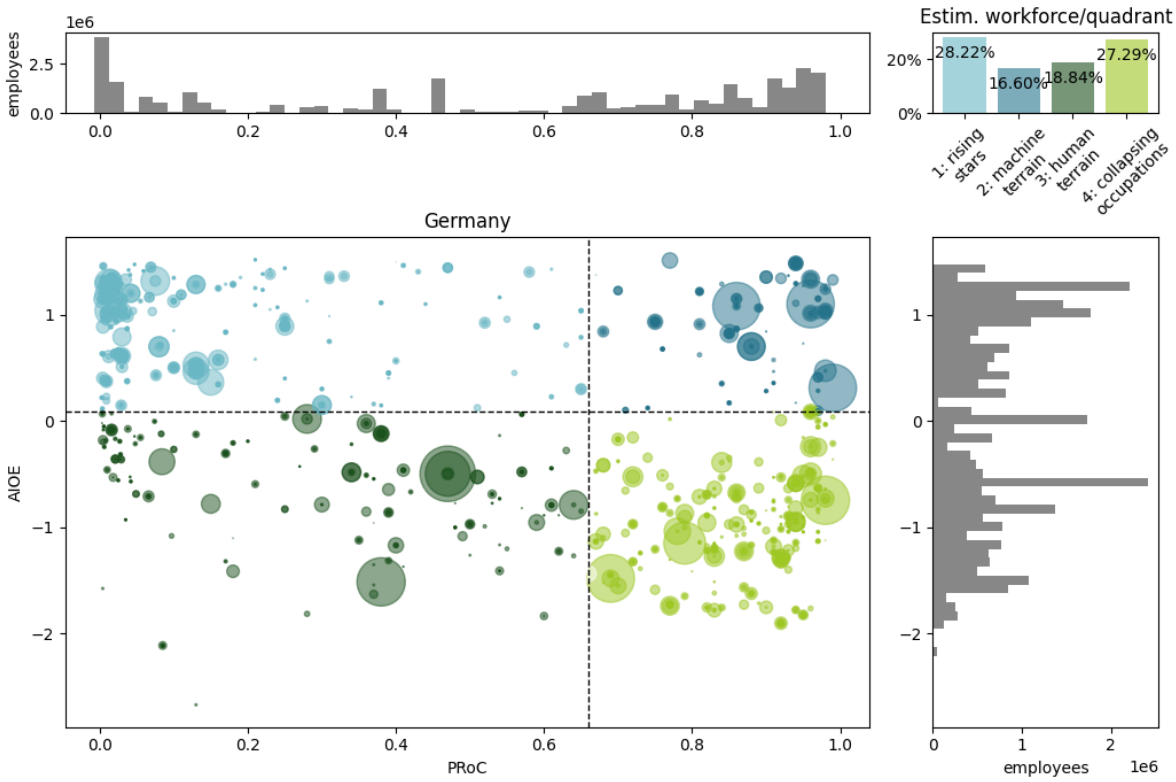


Figure 2: Distribution of occupational groups across the quadrants in the German labour market (source: own elaboration, 2024)

While PRoC scores display a distribution with many values on the both ends of the scale, AIOE follows a more bi-modal shape (as also displayed in Figure 1). Interestingly, a distribution of workers across the same four quadrants is similar throughout the country as either quadrant 1 (in 105, mostly urban districts) or quadrant 4 (in 295 districts) dominate the regional labour markets. There is no German district where workers within quadrant 2 or quadrant 3 make up the relative majority of the workforce.

3.2 Regional level

Figure 3 displays the distribution of workforce across the quadrants in the 400 German districts, presenting regional differences, which are discussed in more detail below.

Quadrant 1 (Rising stars)

While the share of workers in the "rising stars" quadrant is generally higher in urban regions, it is not exclusive to the regions with the largest absolute population sizes. Leading the list is the financial hub of Frankfurt, where 38.59% of employees work within the "rising stars" quadrant, primarily in banking, business organization, and strategy supervisory roles. Interestingly, the financial sector just makes up a smaller part of the workforce in this quadrant. The air travel industry, particularly skilled service roles in air traffic (including flight attendants, ground staff, and cabin crew), also plays a key part.

The air travel sector also boosts the share of first-quadrant workers in Freising (37.13%), which is home to Munich Airport. In Munich itself, a large share of the workforce (36.71%) falls into this category too. Besides this, employees in this quadrant are also assigned to the sectors of business organization and administration, banking, and software development. A good example for the role the IT sector plays within the "rising stars" quadrant is Böblingen (35.06%), a semi-rural district with a high share of skilled workers due to the presence of German headquarters for software companies like HP and IBM.

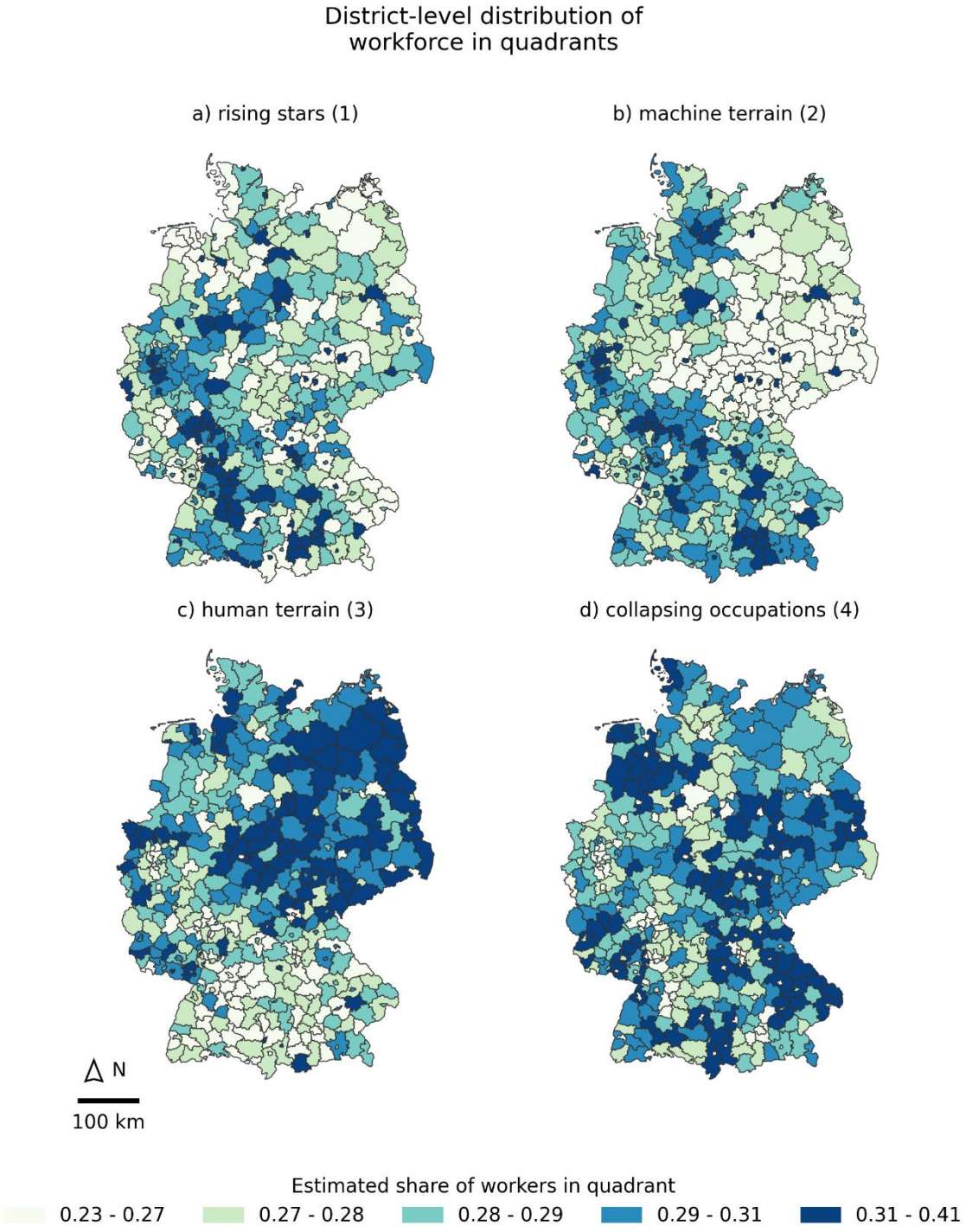


Figure 3: District level distribution of workforce in quadrants (source: own elaboration, 2024)

Other smaller, less populated districts with a high concentration of "rising stars" include Ingolstadt (36.23%), Darmstadt (34.76%), and Karlsruhe (34.62%). These districts are the seats of major companies, such as Audi in Ingolstadt, or have universities with strong technological programs, like the TU Darmstadt and the University of Erlangen–Nuremberg. Conversely, regions with the lowest scores in this quadrant are predominantly rural, such as Hersfeld-Rotenburg (20.79%), Teltow-Fläming (21.65%), and Garmisch-Partenkirchen (21.76%). Hersfeld-Rotenburg has a large share of workers in logistics and warehousing, working for example for Amazon, which operates two fulfilment centres in the area (Amalyze, n.d.). The logistics sector is also established in Teltow-Fläming. Here it is interesting to point out that this district is situated directly south of Berlin, demonstrating a constellation of strong contrasts despite a geographic proximity. In the German capital, 32.36% of the workforce is assigned to the first quadrant.

Quadrant 2 (Machine terrain)

In contrast to the "rising stars" quadrant, occupations in the "machine terrain" quadrant are more closely associated with the country's larger urban regions. Leading the ranking is the Main-Taunus district (28.03%), located next to the financial centre of Frankfurt am Main, followed by Düsseldorf (26.20%), Munich (23.43%), and Bonn (23.37%). However, in neither of these regions has this quadrant the most employees assigned to, in most cases the dominating quadrant is the first one. This suggests that with technological advancement, current population centres might become focal points for both the transformative and destructive effects of digitalisation. At the same time, the share of jobs in the "collapsing occupations" quadrant is relatively low in these districts, which may indicate some resilience of the local labour markets.

At the lower end of the spectrum, this category is more prevalent in rural regions, as seen in the three regions with the lowest scores: Dingolfing-Landau (8.33%), Börde (10.09%), and Sonneberg (10.36%). However, as in the case of regions with high shares of workers working in quadrant 1, we also find an urban region in this collection, namely Emden (10.51%), a small town in Lower Saxony. This district has a North Sea port, a shipyard and features a relatively high share of jobs in warehousing and logistics.

Quadrant 3 (Human terrain)

Higher scores in the third quadrant are mostly found in smaller, yet urban, regional centres such as Herne (26.52%), the above-mentioned Emden (24.47%), and Suhl, Stadt (24.46%). As with quadrant 2, quadrant 3 is also never the dominating one in the German districts. Interestingly, higher shares of the second quadrant are found in regions of the former East Germany, although in no region does the share of workers in this quadrant exceed 27%. In contrast, lower scores are found in the country's larger population centres, such as Frankfurt am Main (12.03%), the district of the city of Munich (12.73%), and region with the same name surrounding the Bavarian capital (12.92%).

Quadrant 4 (Collapsing occupations)

For decision-makers, the "collapsing occupations" quadrant is especially important, which is seemingly more prevalent in the labour markets of rural regions, such as Dingolfing-Landau (37.94%), Börde (36.38%), and Hersfeld-Rotenburg (35.92%). Regions with high shares of workers in this quadrant are spread relatively evenly across Germany and are predominantly rural. However, some mid-sized urban regions also feature a significant share of workers in this category. For example, Neumünster (35.51%) has a relatively high number of employees in the security and warehousing sectors.

Districts with low shares of workers in this quadrant are predominantly urban. These include cities with universities, such as Erlangen (17.80%), Heidelberg (19.37%), and Darmstadt (19.48%), as well as major economic centres like Munich (18.90%), Bonn (19.74%), and Düsseldorf (20.17%). Among the 10 regions

with the lowest share of employees in this quadrant, there are no rural areas represented, and, aside from Jena (19.74%), all are located in former West Germany.

3.3 Limitations

The combination of the two indicators (AIOE/AIGE and PRoC) provides easily interpretable results for assessing labour market transformations on a geographic level. At the same time, it is important to highlight the trade-offs that come with working with indicators that are based on standardised characteristics of occupations.

Occupational groups are difficult to capture in rigid taxonomies. Job roles and tasks vary across sectors and locations. Especially in the field of AI a more universal, skill-based approach to retrieve digitalisation indicators might prove to be more accurate (Frank et al., 2019), and can be used in case studies (Colombo et al., 2019; Lennon et al., 2023). Alternative indicators could also be incorporated, such as the Suitability for Machine Learning (Brynjolfsson et al., 2018), task routinisation (Biagi and Sebastian, 2020), and/or these could be complemented with information obtained through surveys, such as PIAAC (Nedelkoska and Quintini, 2018) to increase their validity even more.

The differences between labour markets in various countries should also be considered, especially when the indicators were developed based on taxonomies in another country than the one they are applied onto. Both the AIOE/AIGE and PRoC indicators relate to the US-labour market, which can be characterised through less strict worker protections and regulations in comparison to Germany. Therefore, we could expect that the transformative and disruptive effects of digitalisation might be unfolding faster in the USA than in Germany.

Regardless, such transformations seem to be ongoing in Germany as well, for example in car manufacturing: Volkswagen in Wolfsburg cited high labour costs as a reason for potential factory closures (Nilsson, 2024). The sector of logistics is also affected, as shown in the layoff of employees in the Amazon fulfilment centre FRA3 in Bad Hersfeld (Meier-Maaz, 2024). This fulfilment centre located in the district Hersfeld-Rotenburg, which features a high share of workers in the fourth quadrant.

Task-based classification offers a snapshot of the current state of jobs but does not predict future developments. Especially the “Future of Employment” report received criticism of generally overestimating the extent of computerisation potentials (Coelli and Borland, 2019; Frey, 2021), due to its premise being computational bottlenecks excluding policy decisions, organisational structures or the willingness of companies to replace workers through computerisation. Additionally, the more detailed the breakdown of tasks linked to an occupation is, the lower the automation potential of a given occupation becomes (Barbieri et al., 2020; Bonin et al., 2015). This means, differences between occupations assigned to different quadrants might be less severe than expected.

Another form of simplification lies in the concepts of "destructive" and "transformative" effects, their mechanisms can be more complex than they appear. Digitalisation can be disruptive for a particular occupational group, but at the same time it can also free its workers from certain duties, enabling them to take on new tasks within the same occupation (Samaan, 2023).

This means that the task distribution between humans and machines are more fluid and flexible, which can be interpreted in both optimistic and pessimistic ways. In this view it is also important to highlight the role of policy decisions and the potentials of job democratisation (such as unions) that might contribute to less severe destructive effects of digitalisation in the labour market (Spencer, 2023).

Data quality also presents a challenge. Regional employment statistics were available only at a relatively broad level for this study. For instance, the third level of the KldB taxonomy includes just 140 categories—

considerably fewer than the 702 classes used by Felten et al. (2021) and Frey and Osborne (2017)—which results in reduced granularity. While the equal distribution approach can assign digitalisation indicators reasonably well, it provides only broad estimations instead of precise predictions.

Furthermore, regional employment data is incomplete, as occupational groups with fewer than 40 employees are excluded from regional statistics. This exclusion affects data granularity, as 109 of the 400 districts have masked data for more than 50 of the 144 occupational groups.

To address this limitation, the available (un-masked) numbers on the third level of the taxonomy were removed from the totals on the second level and and the remaining employess were evenly distributed in across the remaining third level groups. In total 123,183 people in the worforce have been assigned to employment groups using this estimation method, which makes up just 0.36 per cent of the total workforce. Therefore, even with the missing information on the district level, the availably of data does not exercise a significant influence on the validity of the output. Data granularity however still remains an issue.

4 Discussion

Aim of this paper was to present a method for applying occupation-based labour market indicators of digitalisation onto regional labour market statistics. The presented approach is easily replicable and can contriubte to a better understanding of the structures and potential future trends of regional labour markets. Although the findings are preliminary, they reveal important patterns and show a potential for further polarisation of the German labour market at both the regional and the national level.

An interesting topic for further research could be an analysis of interactions between neigbhouring urban and rural regions with vastly different scores. The analysis shows that regions with a dominating role of quadrant 1 are in many cases (urban) ilsands sourrounded by regions where quadrant 4 employs the majority of the work force. A good example for this is the constellation between Berlin and Teltow-Fläming. The German capital shows a clear dominance of Q1 (35.43%) over Q4 (25.03%), while its neighbour, has an opposite distribution of the workforce (Q1 makes up 23.44 and Q4 38.49% of the workforce).

For this reason, further research should also focus on analysing labour market transformations not just at a national scale but also within local contexts. Understanding the structures of the labour market on a regional and local level can be relevant for planners and decision makers, for example in identifying an over-reliance on a a few economic sector or a dominant employer.

Aim of the presented research was to discuss a potentially viable way of projecting digitalisation indicators onto spatial labour market statistics. While the dominance of either quadrant 1 and 4 signalises potential polarisation tendencies within the labour markets, the definition of concrete policy decisions needs deeper, more focussed and local research. This would include additional dimensions of digitalisation, demographic attributes of the labour workforce, the dominance of certain sectors, stakeholders, or companies, or the physical infrastructure located within the regions. However, the presented method can provide a good overview of areas researchers should focus on and dive deeper in when discussing the above mentioned (or further) points and questions.

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