A Digitalised Tourism Sector: Impact on Occupations and Geographies

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Abstract
Tourism plays an important role in the German economy, especially in hotspots in the northern coastal areas and the Alpine regions in the south, where up to 10% of the workforce is employed in tourism-related occupations. Like the broader labour market, these jobs are also affected by digitalisation trends and, as the analysis shows, they may be even more susceptible to certain aspects of it. This article maps digitalisation indicators to occupations and labour market statistics and defines digitalisation profiles that explain how digitalisation shapes employment in the tourism sector and where regional differences in susceptibility may occur.

Keywords: labour market, tourism, artificial intelligence, digitalisation, computerisation

1. Introduction

According to the United Nations World Tourism Organization (UNWTO, 2025), Germany ranked 8th among the world's top 10 most visited countries in 2024, recording 37.5 million international arrivals, an increase of 7.8% compared to 2023. The tourism industry is considered an important pillar of Germany's economy, significantly contributing to both the economy and employment. The World Travel and Tourism Council (WTTC) is forecasting that the sector could grow its annual GDP contribution to nearly € 554 billion by 2034, representing just over 12% of the German economy, and could potentially employ almost 6.5 million people across the country (WTTC, 2024).

Tourism data is sourced from the INKAR database (INKAR, 2024), maintained by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). While cities such as Berlin, Munich and Hamburg attract the most tourists on absolute terms, the relative size of this economic sector is much larger in smaller, less-densely populated regions. Analysis on the level of districts and district-free cities ("Kreise" & "Kreisfreie Städte") shows large disparities in the importance of tourism, illustrated by the three maps on accommodation capacity, demand intensity, and tourism-related employment (Figure 1).

Focusing on the number of tourist beds per 1,000 inhabitants the analysis reveals high concentrations in the northern coastal areas (Baltic Sea and North Sea), the southern Alpine regions, and selected major cities such as Berlin, Munich, and Hamburg.

Tourism-related jobs are concentrated similarly, however some regions with high tourist accommodation capacities exhibit a relatively low share of tourism employment, for example some districts in Rhineland-Palatinate in the southwest of the country. This can result from factors such as reliance on external seasonal labour or a concentration of jobs in other sectors. The analysis of tourism demand, measured by overnight stays per inhabitant, shows some inconsistencies: regions with high accommodation capacity do not always exhibit equally high tourism demand, suggesting an under-utilization of facilities or stronger seasonality.

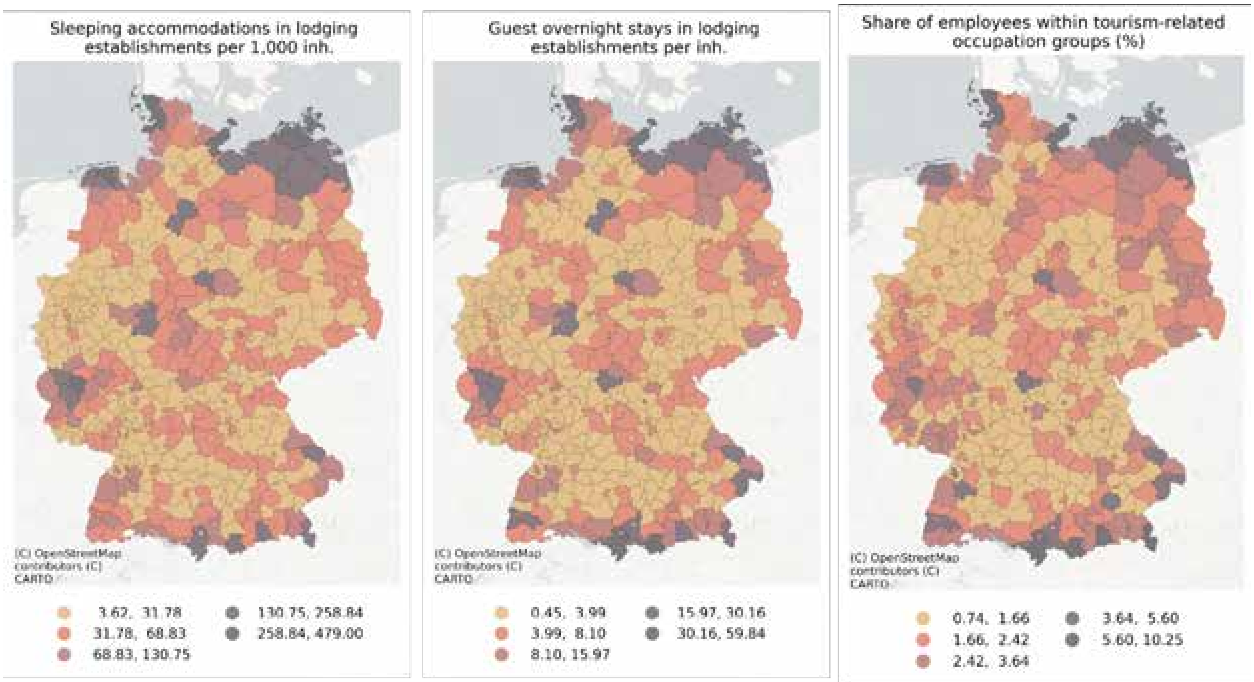


Figure 1. Regional variation in tourism intensity across Germany.

Tourism areas in Germany are not only leisure destinations but also important economic hubs, where tourism contributes to employment, income generation, and regional development. As a cross-sectional industry, tourism intersects with multiple sectors, ranging from transport and accommodation to gastronomy, culture, and business services, making it challenging to assess ongoing trends both statistically and spatially.

In a country where tourism plays a vital economic and cultural role, spanning urban, rural, and natural destinations, there is a growing need for a more integrated and comprehensive understanding of the sector. This article explores the structure, spatial distribution, workforce employments, and technological transformations shaping employment in the tourism sector in Germany.

2. Methods

2.1 Labour Market Information

To quantify and analyse the impact of digitalisation on the tourism sector, labour market data is queried from the employment statistics database (Bundesagentur für Arbeit, 2022) of the German Federal Employment Agency (Bundesagentur für Arbeit). This database consists of a structured list of occupations, occupation groups and sectors, as well as employment numbers per group and geographic entity.

Occupations are organised in a hierarchical system, which is described in the KldB 2010 structure. This occupational taxonomy distinguishes between 36 main occupational groups identified by 2-digit codes (e.g. 63 - Occupations in tourism, hotels and restaurants), which is split up into 140 occupational groups at the 3-digit level (e.g. 631 - Occupations in tourism and the sports (and fitness) industry), and 698 occupational subgroups at the 4-digit level (e.g. 6311 - Management assistants in tourism). On the lowest level in the hierarchy there are 1300 occupations with a 5-digit code (e.g. 63112 - Management assistants in tourism-skilled tasks). The Federal Employment Agency also provides with a list of job titles (with 18,838 entries) that can be linked to these occupations (e.g. jobs linked to occupation 63112 can have titles such as "travel agency assistant", "economic assistant for tourism and foreign languages" or "tourism assistant").

The data used within this research correspond to the reference date of 31 December 2022. Employment numbers are available down to the occupational subgroup (4-digit) level on the federal scale and are differentiated by characteristics such as gender, nationality, age groups, and employment type (full-time, part-time, or marginal employment). At the regional level, data are only available at the level of occupational groups (3-digit), with a differentiation by employment type. This analysis builds up on data of full-time workers who are subject to social security contributions.

The regional breakdown follows the German system of districts and district-free cities (Kreise und kreisfreie Städte), corresponding to the NUTS-3 classification. There are a total of 400 districts and district-free cities, with a median population of 157,406 (INKAR, 2024). Due to data protection rules, occupational groups with fewer than 40 employees are masked in the regional statistics. There are 109 districts with masked data for more than 50 of occupational groups. For these groups, random numbers between 0 and 39 were assigned.

2.2 Data Constraints

A major challenge within this analysis results from the lack of availability of high-quality and disaggregated data, especially in labour market statistics. For instance, the occupational group 631, classified as "Tourism and Sport", includes up to 90 different job titles, ranging from tour guides and alpine guides to managers of travel agencies and graduates with an MBA in tourism economics. These job titles often differ in their qualification requirements, work environments, and digitalisation exposure. This complicates interpreting the impact of digitalisation on the level of occupational groups.

Furthermore, the regional units used in the analysis to obtain the number of workers in a given occupation group are relatively large and often internally diverse. This means that variation in the structure and relevance of the tourism sector may exist within a single district (Sarrión-Gavilán et al., 2015), which cannot necessarily be captured at the available level of resolution. In addition, tourism activities can be expected to produce spillover effects that extend beyond administrative boundaries. These spatial interactions are not reflected in the available data and should be kept in mind when interpreting the results.

2.3 Defining tourism jobs

Tourism is not a closed economic sector and involves a wide range of interactions with other industries. However, the structured and hierarchical nature of available labour market data cannot fully reflect these interdependencies (Liu and Wall, 2006). As a result, certain forms of economic activity are often underrepresented or misclassified, which can lead to a narrower depiction of the tourism sector, as it has been shown in an example in agrotourism (Guizzardi & Costa, 2023).

The classification of workers involved in the tourism sector in Germany by the broader framework of Tourism Satellite Accounts (TSA) is based on tourism-characteristic products and services. These classifications help determine which economic activities are directly or indirectly linked to tourism and, by extension, which types of employment are considered part of the tourism sector. Key tourism characteristic sectors in Germany include accommodation and food and beverage services as primary employers, along with various modes of passenger transport, travel agencies, and cultural, recreational, and sports services, while country-specific products such as health services, food, and fuel reflect additional tourist spending, and other products capture goods and services indirectly linked to tourism consumption (DeStatis, 2024).

Another way to delineate the sector is through activity-based definitions. For example, Melián-González (2025) suggests "accommodation activities; food and beverage service activities; travel agency, tour operator, and related activities" being representative of the tourism sector. Following a more pragmatic distinction, the scope of tourism employment can be interpreted using two complementary concepts: employment in tourism industries and tourism employment (Meis, 2014). The former includes all workers employed in industries that serve both tourists and non-tourists, while the latter focuses on jobs that would not exist, or would exist to a much lesser extent without tourism.

The KldB classification features three occupational categories that match the narrower definition of tourism:

- 631: Tourism and Sport
- 632: Hotel Business (Hotellerie)
- 633: Gastronomy

In order to test whether these three groups can reliably depict occupations in tourism in the narrower sense, the occupational classification was tested with two different methods.

2.3.1. Method 1: Keyword Search in Job Titles
Using the list of 18,838 official job titles, a keyword search was conducted to identify tourism-related occupations. Following keywords were used:

- tour
- hotel
- gast (guest)
- restaurant
- freizeit (recreation)
- camping
- unterkunft (accomodation)
- reise (travel)

Every job title that had one of these (sub-)strings was selected for being related to the tourism industry and was manually checked to exclude misleading results (e.g. “gastroenterology” containing “gast”).

This approach identified 197 job titles, with the following distribution across occupational groups:

- 632 (Occupations in hotels): 62 job titles
- 631 (Occupations in tourism and the sports (and fitness) industry): 47 job titles
- 633 (Gastronomy occupations): 40 job titles
- 293 (Cooking occupations): 7 job titles
- 845 (Driving, flying and sports instructors at educational institutions other than schools): 5 job titles

This analysis shows that a vast majority of tourism employment is adequately captured within the three main occupational groups. Other occupational groups might contain individual occupations, though they are grouped along a large number of other jobs that do not belong to the sector. For example, group 845 includes both recreational sports teachers, but also occupations such as driving instructors. Due to the lack of data granularity, the inclusion of such occupations might lead to skewed results.

2.3.2. Method 2: Correlation Analysis with Core Tourism Groups
In a second method, a statistical correlation analysis was performed to identify occupational groups that consistently co-occur with the three tourism-related occupation groups across districts. The aim was to detect shared patterns that might indicate a functional relationship to tourism.

Occupational groups with correlation coefficients higher than 0.7 were considered relevant. The results are shown in the correlation in Table 1.

Table 1: correlation matrix of tourism-related occupational groups

Occupation group code (Kldb – level 3)	**293**	**631**	**632**	**633**
293 - Cooking occupations	1.00	0.28	0.53	0.89
631 - Occupations in tourism and the sports (and fitness) industry	0.28	1.00	0.57	0.47
632 - Occupations in hotels	0.53	0.57	1.00	0.70
633 - Gastronomy occupations	0.89	0.47	0.70	1.00

While group 293 (Cooking occupations) shows a relatively strong correlation with group 633, its weaker correlation with the other two groups suggests that it is not consistently aligned with core tourism employment patterns. Therefore, the final definition used in this study includes only occupations from groups 631, 632 and 633.

Although this excludes the broader landscape of tourism employment, it offers a focused and consistent basis for analysing tourism-related labour market structures using the available data.

2.4 Definition of digitalisation scores

The evolution of the labour market has been closely linked with technological advancements for centuries. Since the advent of the internet in the 1990s, digitalisation has played an important role in shaping labour market dynamics. Especially in the late nineties and early 2000s, technologies were expected to reduce the importance of physical space, which was signified through concepts such as "death of distance" (Cairncross, 1997). However, the internet and emerging technologies led more to a hybridisation of space (Frith, 2012) instead of a complete relocation of our activities to the virtual world.

The tourism sector is a good example for these hybrid places, with a high importance of physical interaction and real experience at its core, but with an integration of digital tools into related activities. The adoption of modern information and communication technologies (ICT) has significantly enhanced competitiveness and accessibility within the sector, enabling more efficient trip planning and booking, particularly for international travel and among younger age groups (Banescu et al., 2021), but has also been a contributing factor for challenges resulting from the adoption of short-term rental platforms (Bei and Celata, 2023). Immersive technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) can be used as marketing tools (Bogicevic et al., 2019; Tussyadiah et al., 2018) or enhance tourist experience. However, tourism is a sector where the importance of the human context and authentic experiences remain an important factor during the adoption of new technologies (Pencarelli, 2020).

Digitalisation in the workforce within the tourism and hospitality industry can affect the whole guest cycle and has already been adapted by the industry, most for example in the form of social hubs, chatbots, travel assistants or robots (Lukanova and Ilieva, 2019), Currently, technologies are mostly used as a complementary to human labour (Melián-González and and Bulchand-Gidumal, 2025), as automation can also lead to negative reaction from customers, for example in the gastronomy sector (Pancer et al., 2025).

Quantifying the impact of these digitalisation trends and predicting potential future outcomes is currently an unattainable task, even when just focusing a clearly defined set of occupations within a given industry. Public discourse often centres on automation and the anticipated displacement of workers, but these processes are more complex than a simple narrative of job loss. Labour market outcomes are shaped by institutional, organisational, legal, and political contexts (Degryse, 2016; Gordon and Gunkel, 2024). Digitalisation has many different facets and goes beyond a replacement of workers through computers (Acemoglu and Restrepo, 2018; Arntz et al., 2019), which is also true for the tourism sector (Ivanov, 2020).

We can imagine job losses (e.g. through automatic check-in counters in hotels instead of human agents), but potentially alongside with a reorganisation of the content or importance of tasks (e.g. management of bookings on third-party booking platforms before the quests even arrive), the creation of new tasks (e.g. content creation for social media) or even the creation of new jobs (e.g. through an increased need of data analysts in the sector). However, research also finds evidence for a polarisation through automation in the hospitality industry (Yuan and Liu, 2025).

For this reason, measuring the impact of a broad trend such as digitalisation on the labour market is challenging, especially if the aim is to create quantifiable or spatial results. A widely used approach in approximating the effects of this trend is to compare skills or tasks linked to occupation groups towards certain aspects of digitalisation and then depicted as a numeric score. Such scores can be consequently aggregated on the occupational level and linked to labour market statistics. Such methods have been used to assess the effect of digitalisation based on routinisation (Autor et al., 2003), machine learning abilities (Brynjolfsson et al., 2018), teleworkablitiy (Dingel and Neiman, 2020) and (especially more recently) Artificial Intelligence (Colombo et al., 2024; Eloundou et al., 2023; Georgieff and Hyee, 2022).

This paper draws on three such indicators:

- “Artificial Intelligence Occupational Exposure” (AIOE) (Felten et al., 2021)
- “Potential Risk of Computerisation” (PRoC) (Frey and Osborne, 2017), and
- “Digital Competencies Indicator” (DCI) (Lennon et al., 2023),

These indices are described in more detail below.

2.4.1. Artificial Intelligence Occupational Exposure (AIOE)

Artificial Intelligence (AI) is a currently actively discussed topic within the context of labour market transformation. Tools for text and image generation, which were introduced in recent years, have already altered how certain tasks are carried out within occupations. While it remains difficult to quantify the labour market effects of AI or to determine what role AI might play in the future (replacement or reinstatement effects), its significance can be approximated through the AI Occupational Exposure score (Felten et al., 2021). This measure compares the skills associated with occupations in the SOC/O*NET framework to areas of recent AI progress, as tracked by the Electronic Frontier Foundation (EFF).

The EFF dataset identifies advances in specific AI capabilities (e.g. “image recognition”, “language translation”), which are then linked to occupations based on the overlap between these AI capabilities and the human skills required for the job. The AIOE score indicates how exposed an occupation is to AI, based on the similarity between AI capabilities and occupational skill requirements. It is constructed as a relative metric, normalised using the standard deviation of AI-related skill importance and prevalence across occupations. Scores range from -2.67 for dancers to +1.53 for genetic counsellors.

2.4.2. Potential Risk of Computerisation (PRoC)

Another widely debated aspect of labour market digitalisation is the potential replacement of human workers through automation. The probably most well-known attempt to quantify this risk was made in “The Future of Employment” report (Frey and Osborne, 2013, 2017) which assigns a probability of computerisation to specific occupations based on expert assessments on computational bottlenecks. These inputs were used as training data for a machine learning model that estimated scores on an occupational level.
The resulting scores range from 0 to 1, with higher values indicating a greater susceptibility to computerisation. At the low end of the spectrum are occupations such as recreational therapists (score: 0.0028), which consist of

tasks that are hardly automatable. Conversely, 11 occupations, such as telemarketers, data entry keyers, and cargo and freight agents, receive scores of 0.99, indicating a high potential susceptibility to automation. It is however important to note that these numbers can best be interpreted as the highest level of computerisation that is technically possible (Coelli and Borland, 2019; Frey, 2021), without taking the organisational, legal or societal context into account.

2.4.3. Digital Competencies Indicator (DCI)

A third aspect of digitalisation can be identified through the requirements for digital skills for workers within their occupations. Lennon et al. (2023) developed a digital skills indicator using the ESCO database, which links skills to occupations. The indicator builds on an adapted version of the Revealed Comparative Advantage (RCA) statistic, measuring the relative concentration of digital skills within an occupation compared to all others. The analysis distinguishes between essential and optional skills, as well as between narrower and broader definitions of digital skills. Whether a skill is defined to be digital is based on the original ESCO classification (narrower definition), or also through a text analysis of their descriptions (broader definition).

For this study, we use the Digital Competencies Indicator (DCI) based on essential digital skills as defined in the broader sense (Option 3 in the original paper). This avoids overestimating the relevance of digital skills through optional attributes and allows the inclusion of skills not explicitly labelled as digital in the original ESCO taxonomy.

Indicators obtained through this method define 1,269 (42.20%) of the 3,007 occupations requiring no digital skills. The highest scores are defined for database integrators (11.98), digital forensics experts (11.46) and data quality specialists (11.35).

2.5 Indicator matching

While the indicators presented previously provide structured information about certain aspects of digitalisation, they were developed based on a specific occupational statistic and taxonomy with unique definitions of occupation groups and their hierarchical organisation. Germany uses the Klassifikation der Berufe (KldB) system, while the PRoC and AIOE scores are based on the SOC/O*NET taxonomy of the US Department of Labour. The DCI score is linked to the ESCO classification of the European Union.

Although the general structure and logic of these taxonomies are comparable, they define occupation groups differently and also differ in how occupations are grouped hierarchically. During mapping these indicators to geographic statistics, the lack of high-quality regional data is a second issue in the case of this research. Figures are available only on the level of occupational groups (KldB 3-digit level), while the digitalisation indicators are associated with more detailed categories, especially in the case of DCI (3,007 scores need to be mapped to only 140 occupations). As a result, multiple matches are possible between the taxonomies, and direct one-to-one translation is in general not feasible.

To harmonise these systems, crosswalk tables are provided by the maintainers of these taxonomies. In the case case of this study, two conversion tables had to be used, one for matching between the SOC/O*NET and the ESCO taxonomy (Bundesagentur für Arbeit, 2021) and a second one to link the ESCO and the KldB taxonomies (European Commission, Directorate General for Employment, Social Affairs and Inclusion, 2022). This means, the assignment of digitalisation scores is based on a multistep mapping, with in many cases multiple possible linkages.

The classification problem has been discussed in depth in a study of transferring PRoC scores to the German labour market (Bonin et al., 2015), which describes the "equal distribution" approach. Aggregating potential digitalisation scores to a simple number (e.g. taking the average of all potential scores) can result in a gravitation towards the average and masking potentially extreme (but relevant) values. The equal distribution takes all possible scores across a certain occupation group and then divides the number of workers based on the number of potential matches, which enables a better estimation of digitalisation scores, even if data is available only on an aggregated level (Cserpes, 2024).

As the selected indicators use different scales of measurement, the weighted median of these scores were defined to help orientation and relative comparability, following the approach in Fossen and Sorgner (2019). The weighted median across all employees within the employment database (Bundesagentur für Arbeit, 2022) was calculated to be at 0.09 for the AIOE, at 0.66 for the PROoC and at 0.54 for the DCI indicator. Jobs with scores below these thresholds were defined as having low digitalisation scores, and those above as high.

3. Results

3.1. AIOE Scores

Figure 2 displays the AIOE (AI Occupational Exposure) scores for the tourism-related occupational groups. Within the "tourism and sport" group (631), scores tend to be located around the median or above, indicating an overlap between the skills required in these occupations and areas in which AI has made significant progress. An exception in this group is fitness trainers and aerobics instructors, whose low exposure is likely due to the physical and interpersonal nature of their work. This group is included here due to the classification under sport. In contrast, managerial and supervisory roles in tourism show high exposure, suggesting that while customer-facing tasks may remain stable, AI may increasingly support or transform planning, coordination, and back-office functions. Occupations such as tour guides and escorts or event planners fall into a moderate exposure range, indicating partial transformation rather than replacement.

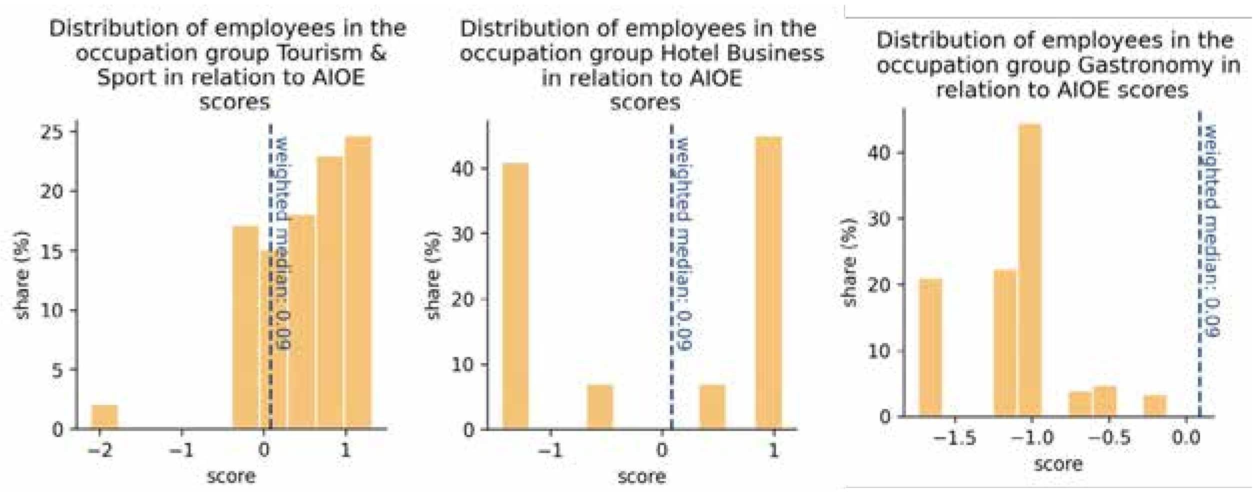


Figure 2. AIOE scores for tourism-related occupations

The hotel business occupational group presents a distribution of AIOE scores on both ends of the spectrum. On the lower end are jobs such as first-line supervisors and janitors, which involve significant managerial oversight or physical labour in areas where application of AI tools is unlikely. Conversely, a substantial portion of workers in this group are in high-exposure roles such as receptionists, administrative clerks, and secretaries who support managerial functions. This suggests that while the core structure of hotels may remain unchanged, the way administrative and support tasks are performed are likely to change due to AI adoption.

In the gastronomy sector, AIOE scores are clearly low, with only a few exceptions (such as food service managers) showing moderate exposure. This implies that, at present, AI is not expected to play a major role in reshaping most gastronomy jobs, which remain heavily reliant on physical presence and interpersonal service.

In summary, the level of AI exposure varies across tourism-related occupations. While workers in the general tourism sector exhibit higher AIOE scores (especially in managerial and planning roles) the hotel business shows a clear divide between supervisory and support roles. Meanwhile, the gastronomy sector appears largely unaffected by AI, at least in the near term.

3.2. PRoC Scores

Figure 3 presents histograms of the Potential for Replacement by Computerisation (PRoC) scores on the national level in Germany. The results indicate a heterogeneous distribution of susceptibility towards computerisation within the occupational group tourism and sport (group 631). Around two-third of the workers in this category can be assigned low susceptibility scores. These include managerial and supervisory positions, as well as occupations such as teachers, instructors, travel agents, and event planners. At the same time, around one-third of employees within this group show higher scores, such as hosts, tour guides and escorts or sales representatives.

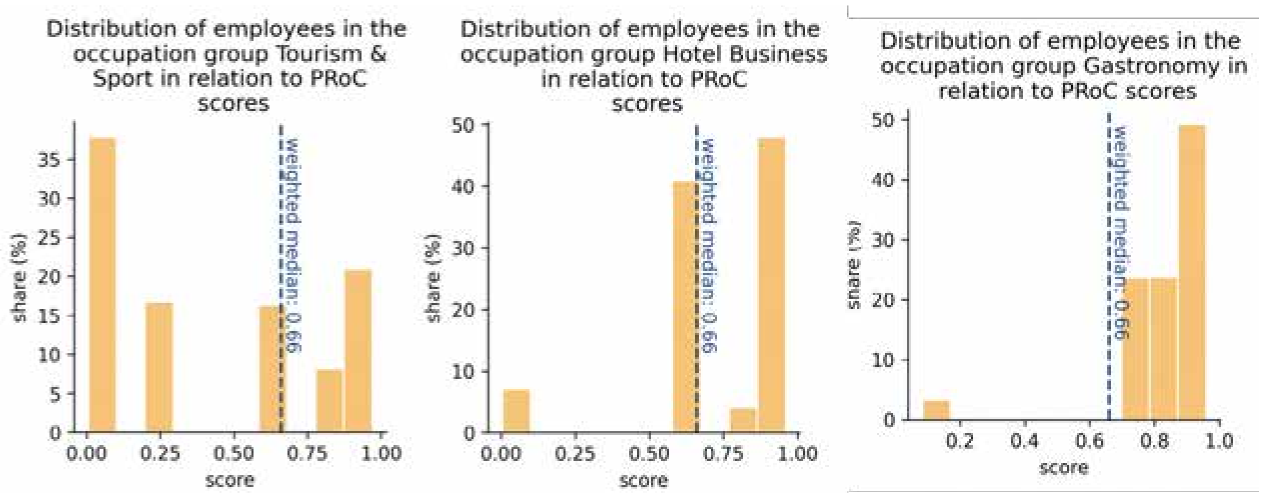


Figure 3. PRoC scores for tourism-related occupations

These findings highlight a central characteristic of task-based indicators such as the PRoC score: they are based on the technical feasibility of automating specific tasks. As such, they reflect the upper bound of automation potential but do not account for factors such as human oversight, social interaction, or customer expectations, which may limit the practical implementation of automation.

In the hotel business occupational group (632), the distribution of scores is more clearly skewed toward a susceptibility level at the median or above. Most jobs in this category, such as receptionists and administrative assistants, conduct tasks that are relatively straightforward to automate. An exception within this group are lodging managers, whose tasks tend to be less automatable due to their complexity and decision-making requirements. This pattern mirrors broader trends, such as the shift from traditional hotels to platforms like Airbnb, where check-in and service functions are largely automated, leaving only maintenance and cleaning staff physically required.

A similar picture emerges in the gastronomy occupational group. Here too, most occupations (such as food preparation workers, waiters, waitresses, and food servers) exhibit high computerisation potentials. Food service managers remain an exception with lower scores. However, despite the technical feasibility, the sector has not fully implemented automation.

In summary, occupations within the tourism sector tend to show different theoretical automation potentials, with higher tendencies within the hotel-business and gastronomy-related roles. However, this potential is not yet fully realised in practice, especially in the gastronomy sector, where human labour continues to play a central role despite the availability of automating technologies.

3.3. DCI Scores

In contrast to the PRoC and AIOE scores, the DCI data is originally available at a more granular occupational level (scores are assigned to 3,007 occupations), allowing for a more precise allocation of scores across occupation groups (Figure 4). Despite this increased level of detail, distinct patterns in the distribution of digital skill intensity still emerge clearly.

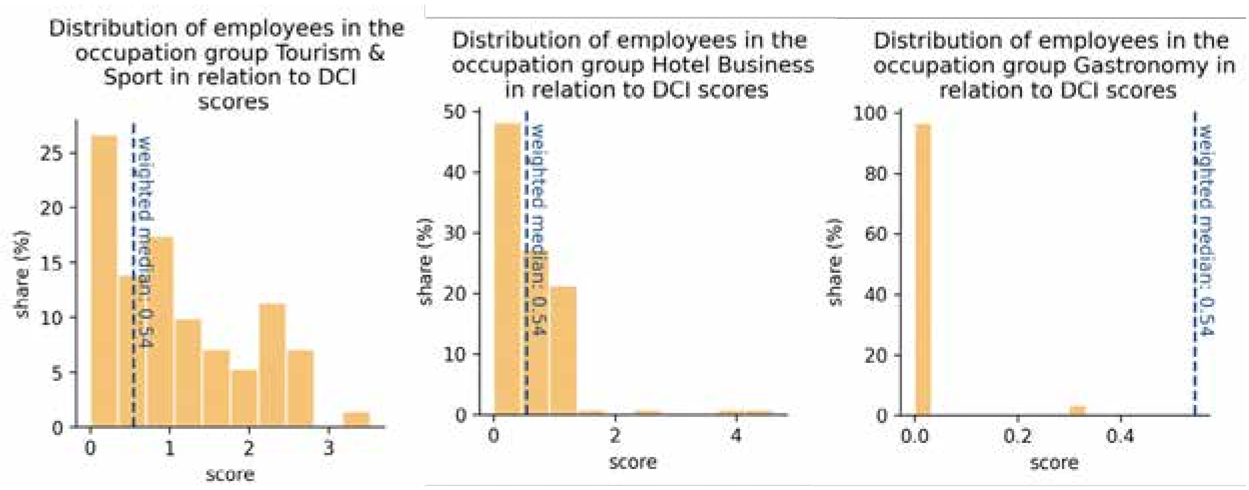


Figure 4: DCI scores for tourism-related occupations

The "tourism and sport" occupational group tends to showcase the largest proportion of workers above the median DCI score. These digital scores are primarily associated with jobs more closely tied to the business and organisational aspects of tourism (such as pricing specialists or customer experience managers). In contrast, roles like travel consultants, tour guides and (somewhat unexpectedly) clerks demonstrate low digital skill levels.

In the hotel business group, the concentration of low DCI scores is even more clear. Exceptions are limited to positions such as administrative assistants and executive assistants, likely due to their involvement in managerial and organisational responsibilities. As expected, occupations such as cleaners and helpers reflect minimal digital skill demands.

Interestingly, even accommodation managers register a DCI score of zero. This can be attributed to the methodology of the DCI, which focuses on essential core skills: in this case, the digital components are outweighed by other core, non-digital skills, suggesting that while digital skills may be present, they are not characteristic to the occupation's core requirements.

The gastronomy sector shows the clearest trend: aside from restaurant managers, nearly all occupations in this group exhibit practically no digital skills according to the DCI.

In conclusion, the findings confirm that the tourism sector is characterised by a contrast in digital skills requirements. There is a clear divide between customer-facing or operational roles and managerial positions, with the latter more likely to involve digital competencies.

3.4. Tourism Digitalisation Susceptibility Score

The selected three digitalisation scores highlight three distinct aspects of this trend, but to provide an overall estimation these indicators need to be analysed in combination. Such combinatory analysis has been applied to analyse AIOE scores per occupation and AI's potential complementarity (Pizzinelli et al., 2023), or through the mapping of occupations based on their PRoC and AIOE scores (Fossen and Sorgner, 2019) and relating them with spatial statistics (Cserpes, 2024). The methodology of this latter study is applied and enhanced in our analysis through the DCI-score as an additional dimension. Every occupation is matched with all possible scores for each of these three digitalisation indicators, then for each occupation the score of high or low is assigned, based on weighted medians of the scores as thresholds.

As an example, the occupation of barkeepers (KldB 6332) can be assigned the AIOE score of -0.62 (below the weighted median), the PRoC score of 0.77 (above) and the DCI score of 0 (below). This leads to the occupational digitalisation profile of low-high-low.

Three digitalisation profiles are particularly relevant for interpretation:

• High across all scores: Occupations with significant digital skill demands, high AI exposure, and high automation potential, likely to transform through digitalisation rather than be replaced (e.g. management assistants in tourism).
• Low AIOE, high PRoC, low DCI: Occupations that are technically automatable but neither heavily exposed to AI nor dependent on digital skills. These represent jobs that could, in theory, be automated but are not currently subject to strong digital transformation pressures (e.g. occupations in system catering).
• Low across all scores: Jobs with minimal digitalisation exposure, usually manual or service-oriented roles. These show limited susceptibility to technological change (e.g. occupations in hotel service).

Table 2 displays the distribution of German workforce across the digitalisation profiles in the whole labour market and within tourism-related occupations. Approximately 20% of all employees within the German labour market work in the low-high-low category, 11% in the high-all group, and another 11% in the low-all group.

Table 2. Overview of digitalisation metrics in tourism vs. the general labour market

AIOE	PRoC	DCI	Share in DE Employment (%)	Share in 631 (Tourism & Sport) (%)	Share in 632 (Hotel business) (%)	Share in 633 (Gastronomy) (%)	Share in all Tourism Occupations (%)
high	high	high	10.59	5.72	24.54	-	6.58
high	high	low	4.51	8.74	-	-	0.79
high	low	low	15.40	29.67	8.44	-	4.76
low	high	low	20.42	2.62	5.63	98.02	66.57
high	low	high	17.31	41.56	-	-	3.75
low	low	high	9.54	0.96	-	-	0.09
low	high	high	11.43	7.86	-	-	0.71
low	low	low	10.81	2.88	61.39	1.98	16.75

When looking at the tourism sector, this distribution is more skewed:

• Around 66% of workers in the tourism sector (especially in gastronomy) are working in an occupation with a low-high-low-profile, indicating technical automatability without current AI relevance or digital competence needs.
• 17% of tourism roles fall into the low-low-low category, including many in hotel maintenance and cleaning, where digitalisation plays a negligible role.

• A small segment (approximately 4%) scores high on all three indicators, mostly administrative or managerial roles in the hotel business, which are not easily replaced but are expected to change through digital processes.

3.5 Geographic distribution

Besides comparing these scores between occupational groups on the national level, understanding their geographic distribution can be a relevant question.

The low-low-low-group (displayed in Figure 5) shows a higher share within the tourism sector than in the general labour market, especially in the districts with high tourism activity in the southern part of the country at the Baltic and Northern Sea coast. This suggests that tourism-intensive regions are currently less strongly affected by digitalisation trends and a large share of their tourism workforce will experience little differences in how they conduct their jobs in future.

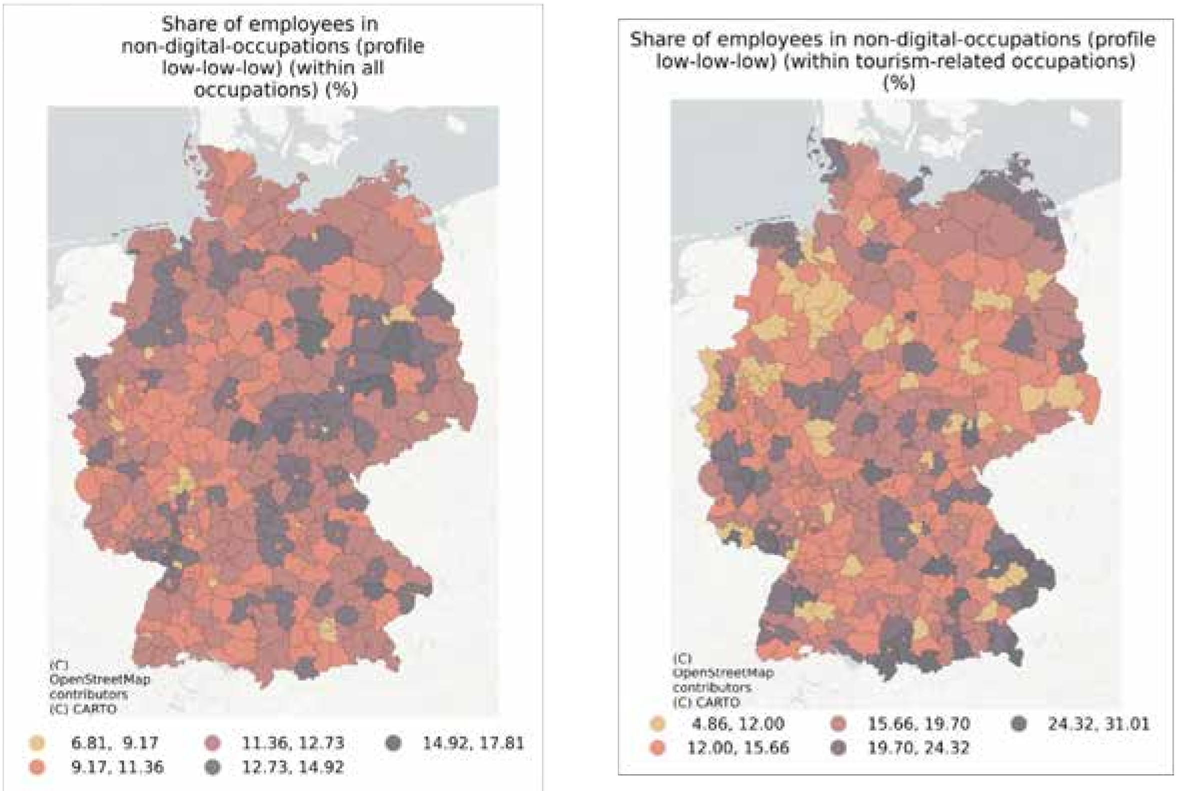


Figure 5. Spatial distribution of the low-low-low group across districts.

At the national level, the high-low-high-group (Figure 6) is the most prevalent, though the overall distribution of categories remains relatively balanced across districts, with some tendencies of urban areas showing lower shares of employees in this category. Within the tourism sector, this category becomes even more dominant. Besides a few exceptions, more than half of the tourism-related workforce has a share of more than 50% within this category, with some regions featuring shares of well above 70%, especially in regions that feature less tourism activity. However, no clear spatial pattern emerges for this category across the country, which suggests that these concentrations reflect local labour market and economic structures rather than broader regional trends or spatial typologies.

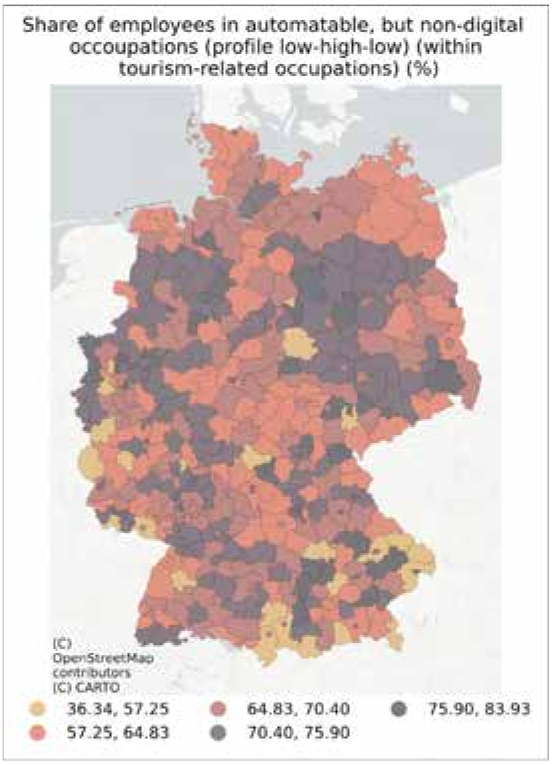
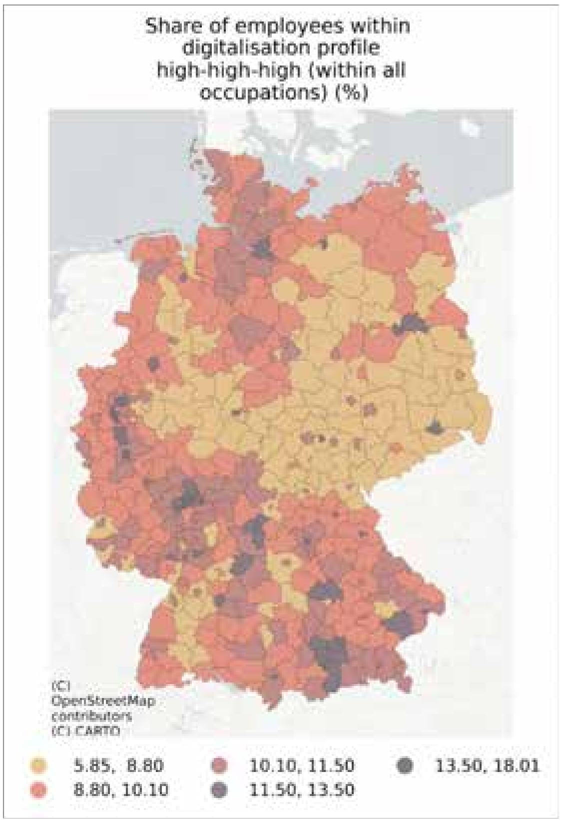


Figure 6. Spatial distribution of the high-low-high group across districts.

Meanwhile, the high-high-high-category (Figure 7) is more concentrated in urban areas, where both general employment and tourism sectors show a stronger presence of digital roles. Although this category is less prominent within tourism occupations compared to the general labour market, the difference is not as clear as with the other two categories. This indicates that digital transformation is affecting some tourism-related roles in a way comparable to broader national trends, particularly in cities.

Overall, the analysis shows that while large parts of the tourism sector remain less digitalised, certain urban areas are seeing a convergence with national trends in digitalisation, particularly in managerial and administrative roles.



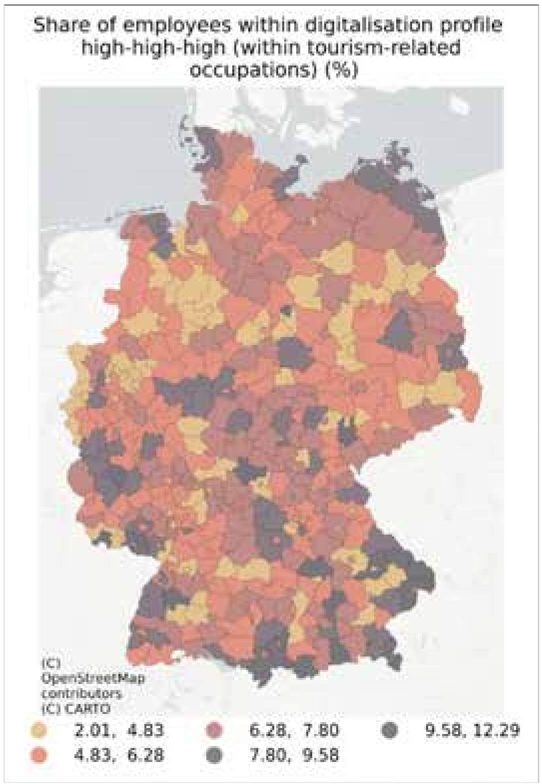


Figure 7. Spatial distribution of the high-high-high group across districts.

3.6. Discussion and outlook

Results of this research show that linking digitalisation indicators to labour market statistics offers a practical way to assess spatial exposure to technological trends. This approach enables a broad, comprehensible overview on both a sectoral (in this case tourism) and spatial level. However, the simplifications involved within this approach come with important limitations that need to be addressed.

The PRoC score, derived from the widely cited "Future of Employment" report, exemplifies both the potential and pitfalls of using quantitative digitalisation indicators. Although this score is useful for identifying technical automation potential, its reliance on expert judgments has been criticised for overestimating susceptibility to automation (Coelli and Borland, 2019; Frey, 2021). The sector of tourism serves as a good example, the occupational group of waiters was assigned a score of 0.94 (meaning high computerisation potential), despite the importance of human interaction in the everyday context (Pancer et al., 2025), which still characterised this occupation. Therefore, the scores presented here should be interpreted with caution, as the highest possible digitalisation potentials technically feasible, without taking the organisational, societal, political or legal context into account.

By incorporating the indicators AIOE and DCI, the composite approach helps to balance some of these overestimations. Nonetheless, each indicator is shaped by the assumptions of its original methodology, and thus still reflects inherent biases. Alternatives such as survey-based data, like PIAAC, can better reflect real-world work contexts, including actual tasks and skills (Georgieff and Hyee, 2021; Nedelkoska and Quintini, 2018). Such survey-based approaches however also come with trade-offs, especially when scaled to broader labour market estimates. Nevertheless, these indicators are only snapshots depicting the current situation and work context and cannot simply be used for future predictions.

For this study, two limitations need to be specifically addressed: the translation across occupational taxonomies and the quality and granularity of available labour market data. Two of the indicators (PRoC and AIOE) originate from a U.S. classification system, which introduces potential mismatches when mapped to the German context. Though crosswalks and weighted distributions help mitigate this, a one-to-one mapping of occupations is hardly possible. More accurate results could potentially be achieved by either reconstructing the indicators using German-specific task or survey data (Bonin et al., 2015; Coelli and Borland, 2019; Georgieff and Hyee, 2021), or by applying the U.S.-based indicators within their original context. However, the occupational-level linkage of indicators remains robust when comparing the relative scores of occupational groups within a single national context (Bonin et al., 2015; Cserpes, 2024).

Second, Germany's regional labour market data is only available at an aggregated level, especially when conducting analysis related to geography. As a result, regional analyses in this paper offer general trends rather than precise local patterns, and should be interpreted accordingly. Finer-grained insights into regional impacts of digitalisation would require alternative data sources, such as targeted surveys or more qualitative elaboration.

From a territorial perspective, a limitation of this study is linked to the spatial resolution of the analysis in terms of referring to functional spatial realities of tourism areas generally overcoming statistical administrative boundaries and addressing analysis to especially in contexts commuting patterns, inter-municipal networks of tourism supply, or mixed economies (Batista e Silva et al., 2018; Li et al., 2018).

Future research should follow a more integrated spatial approach to tourism labour markets. It should focus on the relationship between local economic structures and digital vulnerability. Incorporating variables such as digital infrastructure, smart tourism investments, and public service quality in touristic areas could help to map a geography of tourism resilience, which would be useful for regional planning and targeted policy-making.

Additionally, the perspective to base the analysis on functional tourism networks that transcend administrative boundaries may un-disclose connections between local tourism supply chains and regional patterns of seasonal workers in tourism sector. This approach would enhance the overall understanding of the spatial logic of tourism employment beyond static territorial units.

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