Assessing the Impact of Artificial Intelligence on Germany's Labor Market: Insights from a ChatGPT Analysis

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Abstract

We assess the impact of artificial intelligence (AI) on Germany's labour market applying the methodology on suitability for machine learning (SML) scores established by Brynjolfsson et al., (2018). However, this study introduces two innovative approaches to the conventional methodology. Instead of relying on traditional crowdsourcing platforms for obtaining ratings on automatability, this research exploits the chatbot capabilities of OpenAI's ChatGPT. Additionally, in alignment with the focus on the German labor market, the study extends the application of SML scores to the European Classification of Skills, Competences, Qualifications and Occupations (ESCO). As such, a distinctive contribution of this study lies in the assessment of ChatGPT's effectiveness in gauging the automatability of skills and competencies within the evolving landscape of AI. Furthermore, the study enhances the applicability of its findings by directly mapping SML scores to the European ESCO classification, rendering the results more pertinent for labor market analyses within the European Union. Initial findings indicate a measured impact of AI on a majority of the 13,312 distinct ESCO skills and competencies examined. A more detailed analysis reveals that AI exhibits a more pronounced influence on tasks related to computer utilization and information processing. Activities involving decision-making, communication, research, collaboration, and specific technical proficiencies related to medical care, food preparation, construction, and precision equipment operation receive relatively lower scores. Notably, the study highlights the comparative advantage of human employees in transversal skills like creative thinking, collaboration, leadership, the application of general knowledge, attitudes, values, and specific manual and physical skills. Applying our rankings to German labour force data at the 2-digit ISCO level suggests that, in contrast to previous waves of automation, AI may also impact non-routine cognitive occupations. In fact, our results show that business and administration professionals as well as science and engineering associate professionals receive relatively higher rankings compared to teaching professionals, health associate professionals and personal service workers. Ultimately, the research underscores that the overall ramifications of AI on the labor force will be contingent upon the underlying motivations for its deployment. If the primary impetus is cost reduction, AI implementation might follow historical patterns of employment losses with limited gains in productivity. As such, public policy has an important role to play in recalibrating incentives to prioritize machine usefulness over machine intelligence.

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Introduction

Recent advancements in generative AI, a field of artificial intelligence that focuses on creating computer algorithms that can generate new data in the form of images and text, has the potential to significantly disrupt industries and occupations. Currently the most prominent example of an application of generative AI probably is OpenAI's ChatGPT.[2]

Similar to the steam engine, electricity or semiconductors, generative AI is perceived as a general purpose technology (Eloundou et al., 2023). General purpose technologies, GPTs in short, are commonly at the start of technological revolutions with the potential to disrupt the entire economy (Bresnahan and Trajtenberg, 1995). According to Jovanovic and Rousseau (2005), GPTs possess three key attributes. They stimulate subsequent waves of derivative innovations, each tailored to specific sectors of the economy. In addition, these technologies undergo continuous improvement, resulting in a progressive reduction in costs for end-users. Lastly, their impact permeates across all sectors of the economy.

The disruptive nature of GPTs on the economy raises the question to what extent generative AI is going to affect labour markets, specifically regarding the potential ramifications for skills, competencies and occupations.

The Impact of Technology on Skill Demand

The notion of skill-biased technological change has emerged as a widely accepted framework to study the impact of technology on labour dynamics. This conceptual framework traces its origins to the seminal research conducted by Katz and Murphy (Lawrence F. Katz and Kevin M. Murphy, 1992), who find that technological advancements invariably elevate the demand for skilled labour in comparison to unskilled labour.

[2] GPT here stands for "Generative Pre-trained Transformer." In essence it is an advanced type of neural network where the "Pre-trained" aspect means that it has been initially trained on a vast amount of data to learn general language patterns, and then fine-tuned for specific tasks like chat-based conversations.

Building on this, subsequent studies have analysed the impact of automation on occupations at the skill and task level, distinguishing between routine and repetitive tasks on one hand, and non-routine tasks on the other (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019; Autor et al., 2003). Empirical findings suggest that automation exerts adverse effects on routine tasks while bolstering non-routine cognitive tasks, displaying a relatively neutral impact on non-routine manual tasks.

Several studies have additionally confirmed a correlation between automation and income inequality (Acemoglu and Restrepo, 2022; Hidalgo-Pérez and Molinari, 2021; Korinek and Stiglitz, 2021; Van Reenen, 2011). The results imply that automation and technological advancements contribute to wage disparities by enhancing the productivity of non-routine cognitive-intensive occupations, while simultaneously displacing human labour in routine task-intensive occupations.

The Impact of AI on Labour and Skills

In contrast to earlier digital technologies that primarily automated occupations characterized by routine tasks, artificial intelligence (AI) as a predictive technology likely affects a broader spectrum of non-routine tasks across diverse occupational domains. This is due to the fact that AI technology excels in tasks that involve pattern detection, judgment-making, and optimization.

A nascent yet rapidly expanding body of literature has emerged, employing a task-based approach to examine the implications of AI adoption on different occupations (Acemoglu, Autor, et al., 2022; Brynjolfsson et al., 2018; Felten et al., 2019; Webb et al., 2020). In general, these studies apply methodologies to ascertain the specific worker tasks that AI can potentially automate and those that it cannot. Overall, empirical findings indicate that AI has the potential to increasingly take on more complex tasks mainly performed by high-skilled workers.

Assessing the potential impact of generative AI on labour and skills, Brynjolfsson et al. (2023) conduct a comprehensive investigation into AI-based conversational assistants on customer support agents. Their results suggest a notable enhancement in productivity, particularly among newly hired employees and low-skilled individuals. Furthermore, the implementation of AI

assistance appears to yield improvements in customer satisfaction, leading to a reduction in requests for managerial intervention and an increase in employee retention rates.

Similarly, Noy et al. (2023) examine the utilization of generative AI in an experiential context, specifically in relation to the completion of writing tasks. Their research highlights the positive influence of AI tools on participant productivity. By restructuring human tasks to prioritize idea generation, the findings suggest that the adoption of AI technology contributes to heightened job satisfaction among individuals.

Recent empirical evidence, then, indicates that AI, in contrast to previous waves of technological change, might positively impact the productivity of lower skilled workers with a potential to reverse the phenomenon of skill-biased technological change (Agrawal et al., 2023)

That said, it is poised to significantly change the nature of work. Assessing the potential impact of OpenAI's GPT-4 on occupational tasks and work activities in the United States, Eloundou et al. (2023) combine data from O*NET with employment and wage data for roughly 1,000 occupations. Their findings show that approximately 80% of the American workforce could experience a minimum 10% alteration in their work tasks as a result of the introduction of generative AI. Furthermore, approximately 19% of the workforce may encounter substantial changes, with at least 50% of their tasks being affected by the integration of AI technologies.

Largely in line with these results, a recent study by Lane and Saint-Martin (2021) finds that AI will likely lead to an increased reorganization of tasks within occupations rather than a reduction in employment and wages.

Methodology

This paper contributes to the existing literature assessing the impact of AI on skills, competencies and occupations. Specifically, it adopts the approach developed by Brynjolfsson et al. (2018) to establish the suitability for machine learning (SML) for tasks performed by human workers. In so doing, we generate SML scores that measure the level of AI's capability in assuming particular tasks or displacing specific skills. Tasks and skills are ranked at a scale from 1 (not automatable) to 5 (fully automatable).

We depart from the approach introduced by Brynjolfsson et al. (2018) in two key aspects. First, instead of using crowdsourcing platforms to obtain ratings for automatability, we utilize OpenAI's ChatGPT. By leveraging ChatGPT's access to vast knowledge on the Internet, we obtain ratings for specific tasks, skills and competencies using its chatbot capabilities. The ratings thereby reflect the capability of AI to perform a given task. Second, we focus on evaluating AI's impact on German occupations using the European Classification of Skills, Competences, Qualifications and Occupations (ESCO) database. ESCO provides a comprehensive framework encompassing over 3,000 distinct occupations and 13,890 skills, including skills related to abilities, personal attributes, knowledge, and interests.

The reliability of ratings obtained from a chatbot depend on three major factors. First, overall results can differ by how the question, or prompt, is formulated. Thus, identifying the appropriate prompt is crucial for our analysis. The more detailed the prompt, the more precise the output provided by the chatbot.

In addition to the prompt itself, two additional parameters are of importance when generating chatbot responses.[3] First, the so-called temperature is a parameter that affects the randomness of the model's responses. In other words, it controls the level of diversity in the answers. Temperature parameters closer to 1 or higher lead to more diversity in responses but can also generate nonsensical or irrelevant answers. In contrast, a temperature closer to 0 makes the output more deterministic and focused. As a rule, temperatures of 0.7 and higher are recommended for creative writing or exploratory code writing.

The second parameter of importance is the so-called 'top_p' parameter. Simply put, whenever ChatGPT generates text, it needs to choose the next word to add. The model has different options for what the next word could be, and it needs to decide which one to pick. The 'top_p' parameter influences how many options it should consider. Assume the 'top_p' value is set to 0.1. This means the model will only look at the words that make up the top 10% of the most likely options.

[3] See, for example, the Open AI quick start documentation at https://platform.openai.com/docs/quickstart.

In short, the closer the 'top_p' value is to 0, the narrower the choices for the next answer the higher the focus on the most probable output.

Having tested a variety of settings with regard to prompts, temperature and 'top_p' settings, we find that the following settings provide the most reliable and consistent responses. As the chatbot engine we use text-davinci-003. According to OpenAI, text-davinci-003 is a GPT-3 model trained on human feedback. Compared to earlier models, it generates clearer content and can handle more complex instructions.[4] Our final prompt to the chatbot is the following

> "*Nimm an Du bist ein Experte für Künstliche Intelligenz: Als solcher bewerte die Automatisierbarkeit folgender Fähigkeit auf einer Skala von 1 bis 5, wobei 1 für nicht automatisierbar und 5 für sehr automatisierbar steht. Als Antwort gib bitte NUR EINE reine Zahl! '{skill}*"[5]

As we are seeking to receive more focused and coherent responses, we set temperature to 0 and 'top_p' to 0.1.

To further test the reliability of responses, we prompt the chatbot for explanations on a sample of the rankings provided. This helps to gain insights into the "reasoning" behind the responses. For example, when we ask why the skill "develop employment policies" receives a rating of 1 on our scale, ChatGPT provides the following explanation:

> *"While technology can assist in data analysis and policy formulation, the multifaceted nature of employment policies requires human involvement. Developing effective policies entails understanding socio-economic factors, labor market dynamics, and stakeholder perspectives. It involves considering diverse perspectives, balancing competing interests, and addressing social and ethical implications. Additionally, employment policies need to align with broader social goals, address inequalities, and ensure fairness. Human judgment and expertise are critical in interpreting complex data, incorporating social nuances, and making informed decisions. Therefore, while technology can support the policy development process, human involvement remains essential for effective and inclusive employment policies."*

[4] See https://help.openai.com/en/articles/6779149-how-do-text-davinci-002-and-text-davinci-003-differ.
[5] Since we generate results for the German labour market, our prompt is in German. In English it translates to the following *"Assume you are an expert in artificial intelligence: As such, rate the automatability of the following skill on a scale of 1 to 5, where 1 is not automatable and 5 is highly automatable. As an answer please give ONLY ONE pure number! '{skill}'"*

Similarly, when asking about the reason for a rating of 5 for the skill "maintaining transaction's records" we obtain this explanation:

> *"With advancements in financial technology and automated systems, tasks related to transaction reporting can be efficiently handled by machines. Automated systems can accurately record and process transaction data, perform reconciliations, and generate reports. This reduces the need for manual data entry and manipulation, improving efficiency and reducing human error. However, some level of human oversight and interpretation may still be required for complex or exceptional cases, ensuring data accuracy and compliance with regulatory requirements. Nonetheless, the overall process of maintaining transaction reports can be largely automated, allowing human resources to focus on higher-value activities such as data analysis, decision-making, and strategic planning."*

Results

The Impact of AI on Skills

Figure 1 summarizes the scores for a total of 13,312 ESCO skills and competencies obtained from OpenAI's GPT 3.5. As is shown, 38% of all skills and competencies assessed receive a ranking of 3, which we could interpret as a moderate risk from an impact of AI. Interestingly, almost 55% of skills and competencies are rated at low (43.4%) or very low risk (11.8%). In contrast, around 7% are rated to be at high (5.8%) or very high (1.0%) risk from being negatively impacted by AI.

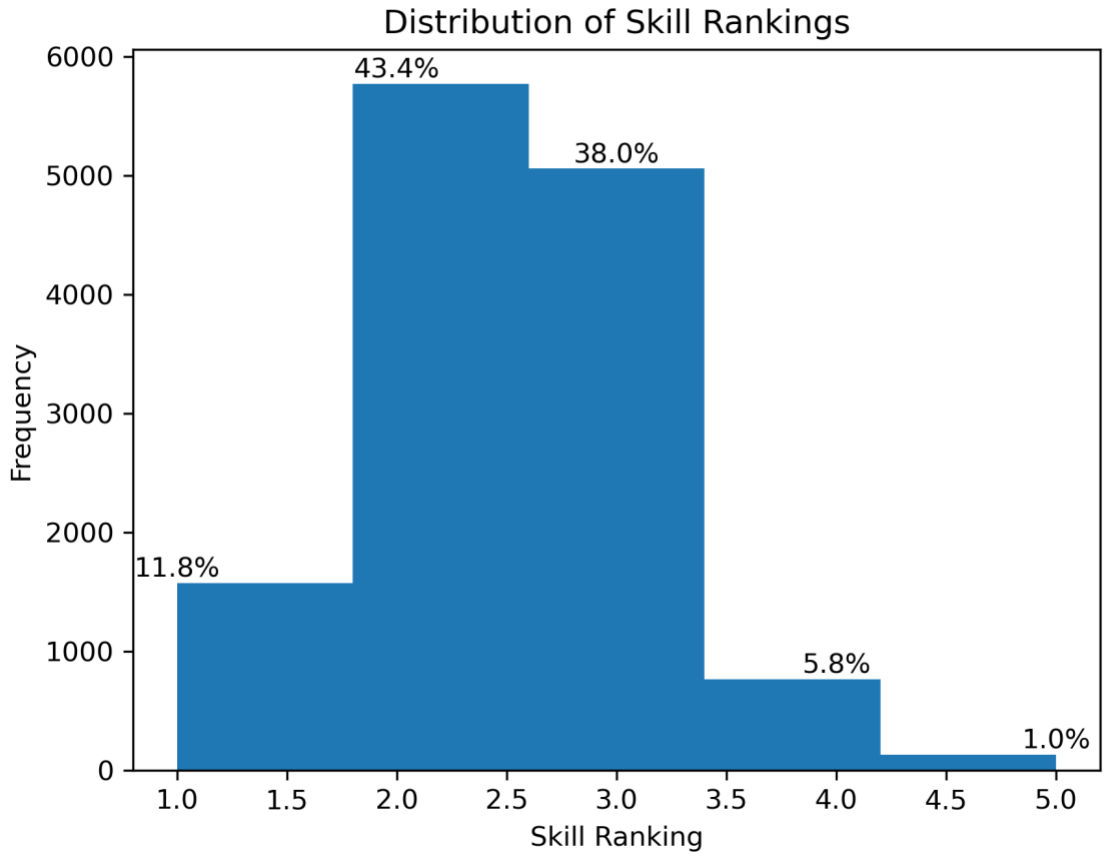

Figure 1: Distribution of ratings for ESCO skills and competencies.

The Impact of AI on Skill Categories

Additional information available on the ESCO website allows us to dig a little deeper into the likely impact of AI on skills and competencies. Specifically, ESCO distinguishes between the following categories, or domains, of skills and competences: 'Knowledge', 'Language skills and knowledge', 'Skills' and 'Transversal skills and competences'. Each category is then further broken down into specific areas. Appendix 1 provides a summary and description for all sub-categories used in our analysis and their associated tasks or lower-order sub-categories.

Retrieving the additional information and explanation on the hierarchy provided for each skill and competency from the relevant web pages, we first assign each observation into the main applicable category. In a second step, we assign each skill to the appropriate second-order sub-category. For example, the domain 'Skills' is divided into eight sub-categories one if which is

‘Management Skills (S4)’. This sub-category is then further divided into ten second-order sub-categories or tasks, including, for example, ‘Making decisions’ and ‘Supervising people’.

Starting with the ‘Skills’ domain, Figure 2 shows the average rankings for the eight different sub-categories. Here, the sub-category ‘S5-Working with computers’ receives the highest score (3.09), followed by ‘S2-Information skills’ (2.69), which contains tasks such as managing information, processing information, and calculating and estimating. ‘S6-Handling and moving’ receives the lowest rating of 2.07. It contains tasks such as moving and lifting, tending plants and crops, and using hand tools. Among the ‘Skills’ domain, ‘S3-Assisting and caring’ receives the second-lowest ranking of 2.16. It includes tasks such as counselling, providing health care and medical treatment and providing general personal care.

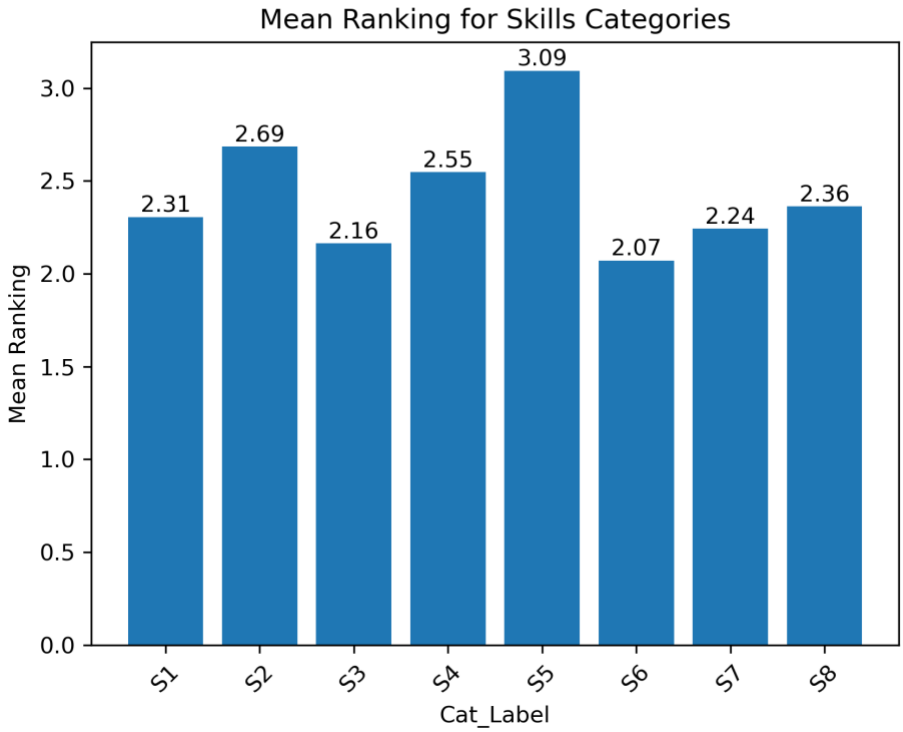

Figure 2: Average Rankings for the ESCO ‘Skills’ Domain.

From Figure 2 it appears that the skill categories ‘Working with Computers’, ‘Information Skills’ and ‘Management Skills’ are relatively more impacted by AI than the remaining categories. Since the skills hierarchy within the ESCO database allows us to disaggregate these skill

categories further, we next generate mean rankings for each of these sub-categories. This enables us to assess the task level within each sub-category. For example, the sub-category 'S1-Communication, Collaboration and Creativity' consists of 15 second-order sub-categories, or tasks, ranging from 'Teaching and training' to 'Using more than one language'. As Figure 6 in Appendix 2 shows, there is some variety regarding the impact of AI on these different tasks. For example, the mean ranking for 'Teaching and training' is 1.98 whereas 'Using more than one language' receives an average rating of 2.93.

Similar variety exists within all skill categories. As Table 1 shows, the standard deviations among tasks within skill categories range from 0.21 in 'Constructing' to 0.35 in 'Information Skills'. The higher value in 'Information Skills' is due to the fact the included tasks differ significantly. For example, the mean ranking for 'Conducting studies, investigations and examinations' is 2.3 and that of 'Monitoring developments in areas of expertise' 2.54. In contrast, 'Managing information' receives an average ranking of 3.12 and 'Calculating and estimating' an average ranking of 3.02.

Table 1: Mean and Standard Deviations for Task Rankings by Skill Category.

Skill Category	**Mean**	**Std. Dev.**
S1-Communication, Collaboration and Creativity	2.34	0.25
S2-Information Skills	2.85	0.35
S3-Assisting and Caring	2.07	0.27
S4-Management Skills	2.50	0.24
S5-Working with Computers	3.13	0.23
S6-Handling and Moving	2.14	0.29
S7-Constructing	2.12	0.21
S8-Working with Machinery and Specialised Equipment	2.50	0.32

The overall implication here might be that if AI takes over tasks with a relatively higher rating, the task composition of occupations performed by humans might shift towards those with an overall lower rating. As Figures 7 to 14 in Appendix 2 show, these include activities related to decision-making, communication, research, and collaboration as well as specific technical skills with regard to medical care, food preparation, construction, and the operation of precision equipment.

Next we consider the ‘Transversal skills and competences’ domain. According to ESCO, these include skills and competencies not specifically related to a particular occupation or knowledge area and can thus be applied in a wide variety of work, learning or life activities (Hart et al., 2021).

As Figure 3 shows, sub-category ‘T2-Thinking skills and competences’ which includes tasks such as processing information, ideas and concepts and planning and organising, receives the highest ranking (2.8), followed by ‘T3-Self-management skills and competences’ (2.65). Sub-category ‘T1-Core skills and competences’, which includes language and numeracy skills, has the lowest average rating among this group (1.96).

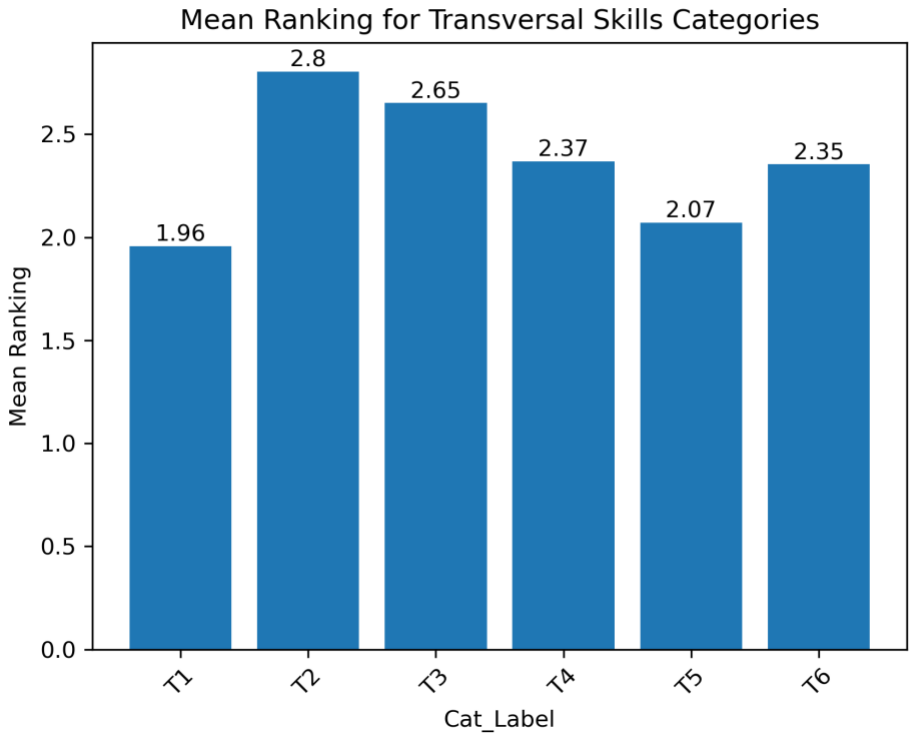

Figure 3: Average Rankings for the ESCO ‘Transversal skills and competences’ Domain.

Again, we separately assess the tasks related to these skill-subcategories. The average rankings for these tasks are illustrated in Figures 15 to 20 in Appendix 2. For example, category ‘T1-Core Skills and Competences’ includes ‘Mastering languages’ with a mean ranking of 1.82, ‘Working with numbers and measures’ with a mean ranking of 3 and ‘Working with digital devices and applications’ with a mean ranking of 3.2.

As Table 2 shows, the range in standard deviations in transversal skills is larger compared to that of the regular skill categories in Table 1. Standard deviations are fairly low for 'Physical and manual skills and competences' as well as 'Self-management skills and competences'. In contrast, 'Core skills and competences', 'Life skills and competences' and 'Thinking skills and competences' demonstrate relatively larger standard deviations. The latter category includes, for example, 'Thinking creatively and innovatively' with a mean rating of 2.09 and 'Planning and organizing' with a mean rating of 3.05. With regard to transversal skills and competences it appears that human employees have a comparative advantage in skills related to creative and innovative thinking, collaboration and leadership, the application of general knowledge, attitudes and values, and specific manual and physical skills.

Table 2: Mean and Standard Deviations for Task Rankings by Transversal Skill Category.

Transversal Skill Category	**Mean**	**Std. Dev.**
T1-Core Skills and Competences	2.67	0.75
T2-Thinking Skills and Competences	2.64	0.42
T3-Self-management Skills and Competences	2.61	0.15
T4-Social and Communication Skills and Competences	2.40	0.20
T5-Physical and Manual Skills and Competences	2.09	0.12
T6-Life Skills and Competences	2.41	0.44

Figure 4 shows average scores for the ESCO 'Knowledge' domain. Among these, 'K8-Information and communication technologies (icts)' has the highest average rating (3.43), followed at some distance by 'K5-Engineering, manufacturing and construction' (2.57) and 'K3-Business, administration and law' (2.53). 'K7-Health and welfare' receives the lowest average rating in the 'Knowledge' domain (1.95). Welfare here includes aspects such as care of the elderly and of disables adults, social work and counselling as well as childcare and youth services.

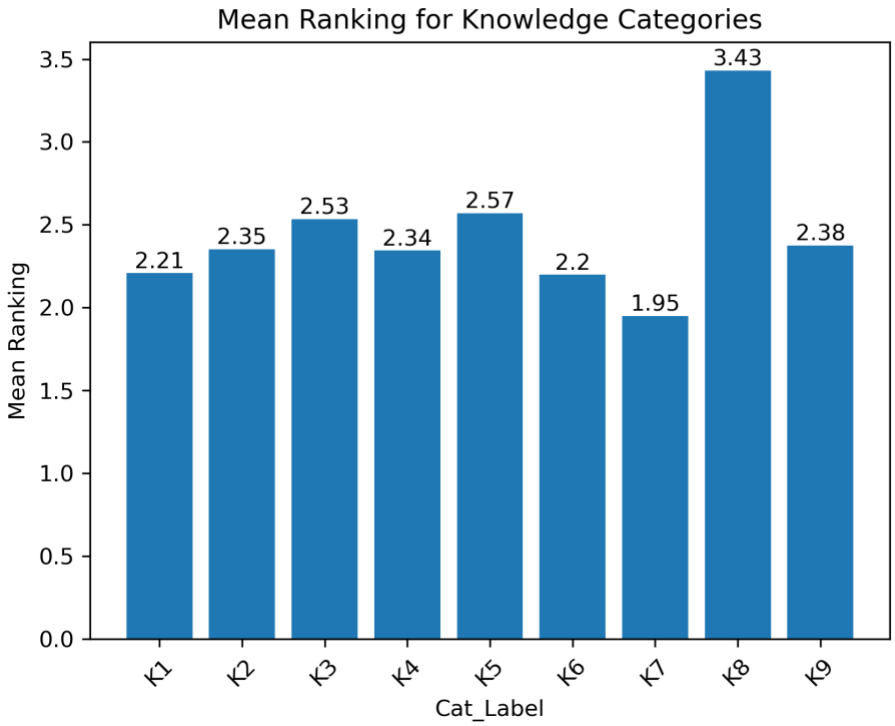

Figure 4: Average Rankings for the ESCO 'Knowledge' Domain.

The Impact of AI on Occupations and Employment

In a final step, we aggregate the rated skills and competencies over 2,937 unique occupations. We thereby use the essential skills per occupation, as provided by the ESCO classification and calculate the average score for each occupation. The results are illustrated in Figure 5. Average scores range from 1.4 to 4.4. That said, almost 81% of all observations fall between a rating of 2.0 and 2.8 with an additional 15% between 3.0 and 3.8.

In fact, only two occupations have essential skills with an average rating of 4.0 and higher. Appendix 3 shows the occupations with the ten highest and ten lowest average ratings based on their essential skills.

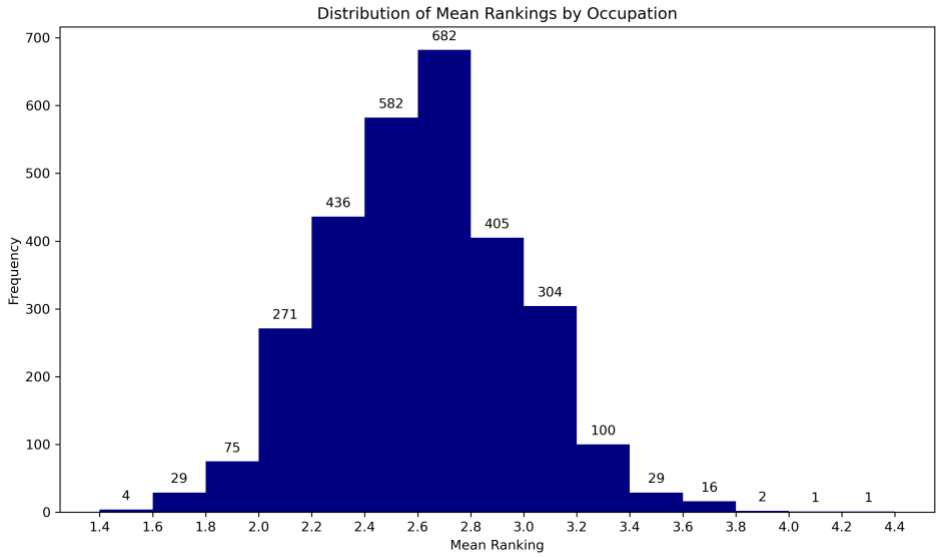

Figure 5: Average Ratings for by Occupation based on Essential Skills.

To estimate what this might mean for employment in Germany, we combine our ratings with occupational employment data at the 2-digit ISCO level. Table 3 shows the top 10 occupations in Germany by employment share with their respective rankings. Combined, these 10 occupations account for roughly 53% of total employment.[6] As Table 3 illustrates, among Germany's top 10 occupations, average rankings are highest for general and keyboard clerks (3.09) and sales workers (2.81). Yet, business and administration professionals, business and administration associate professionals and science and engineering associate professionals also receive relatively higher mean rankings. In fact, among the top 10 occupations by employment share, the occupations with the lowest mean rankings are teaching professionals, health associate professionals and personal service workers. This is in line with some recent literature that, in contrast to previous waves of automation, the impact of AI might differ with regard to its impact on non-routine cognitive occupations (Lane & Saint-Martin, 2021).

[6] See Appendix 4 for the table including all occupations.

Table 3: Top 10 Occupations at 2-digit ISCO level by Employment Share with Mean Rankings. Source: Eurostat, Employed persons by detailed occupation (ISCO-08 two digit level); Product Code: lfsa_egai2d.

ISCO	Berufsbezeichnung	Occupation	Employment Share (%)	Mean Ranking
OC33	Nicht akademische betriebswirtschaftliche und kaufmännische Fachkräfte und Verwaltungsfachkräfte	Business and administration associate professionals	7.06	2.68
OC41	Allgemeine Büro- und Sekretariatskräfte	General and keyboard clerks	6.61	3.09
OC32	Assistenzberufe im Gesundheitswesen	Health associate professionals	6.31	2.35
OC23	Lehrkräfte	Teaching professionals	5.91	2.39
OC52	Verkaufskräfte	Sales workers	5.88	2.81
OC72	Metallarbeiter, Mechaniker und verwandte Berufe	Metal, machinery and related trades workers	4.68	2.58
OC51	Berufe im Bereich personenbezogener Dienstleistungen	Personal service workers	4.47	2.32
OC31	Ingenieurtechnische und vergleichbare Fachkräfte	Science and engineering associate professionals	4.33	2.63
OC21	Naturwissenschaftler, Mathematiker und Ingenieure	Science and engineering professionals	4.27	2.55
OC24	Betriebswirte und vergleichbare akademische Berufe	Business and administration professionals	4	2.68

That said, the impact of AI on occupations will ultimately depend on the specific motivations for its deployment. As Acemoglu and Johnson (Acemoglu & Johnson, 2023) point out, in the US automation was often implemented to cut labour costs with adverse effects on the labour force and only limited benefits to productivity. In contrast, automation in Germany often led to the retraining of the existing workforce with positive effects on marginal productivity. According to the authors, a crucial reason for the different impact of automation on the labour force in these two countries is the incentive structure with regard to taxation and labour regulation as well as the share of business school educated managers. With regard to the latter Acemoglu et al. (2022) find that business school-educated managers pay lower wages, stop sharing rents, and have significantly contributed to the decline in the labor share and

slowdown of median wages. In the context of AI, then, Acemoglu and Johnson suggest that a focus should be on machine usefulness – i.e. how useful machines are to humans – rather than machine intelligence. Public policy has a role to play here in setting the incentive structure to accomplish this.

Conclusion

We assess the impact of artificial intelligence (AI) on Germany's labour market applying the methodology on suitability for machine learning (SML) scores established by Brynjolfsson et al., (2018) using two novel approaches. First, as opposed to using crowdsourcing platforms to obtain ratings for automatability, we utilize OpenAI's ChatGPT's chatbot capabilities. Second, since we are interested in the impact on the German labour market, we apply SML scores to the European Classification of Skills, Competences, Qualifications and Occupations (ESCO).

As such, we contribute to the literature by assessing the effectiveness of ChatGPT to rate the automatability of skills and competencies in the context of recent developments in AI. Further, we apply our ratings to the European ESCO classification thereby making our results more relevant to EU labour market analyses.

Our first results on the potential impact of AI on 13,312 unique ESCO skills and competencies indicates a moderate impact of AI on the majority of skills as only around 6% receive a rating of 4 or higher. Digging deeper, we create skills and knowledge categories utilizing additional information available from ESCO web pages. Here, our findings show that tasks related to working with computers and information processing generate higher scores compared to tasks related to assisting and caring or handling and moving. Knowledge domains related to information and communication technologies, engineering, manufacturing and construction, and business, administration and law also receive higher scores when compared to those related to health and welfare or arts and humanities.

Assessing the impact on skills and tasks in more detail reveals that activities related to decision-making, communication, research, and collaboration as well as specific technical skills with regard to medical care, food preparation, construction, and the operation of precision equipment

have relatively lower scores. Similarly, a detailed assessment of transversal skills and competences suggests that human employees have a comparative advantage in skills related to creative and innovative thinking, collaboration and leadership, the application of general knowledge, attitudes and values, and specific manual and physical skills.

In a final step, we aggregate our results to occupational levels assessing the impact of AI on essential skills by occupation for a total of 2,937 occupations. Here we find that almost 81% of all observations fall between a rating of 2.0 and 2.8 and an additional 15% receive a score between 3.0 and 3.8.

Applying our rankings to German labour force data at the 2-digit ISCO level suggests that, in contrast to previous waves of automation, AI may also impact non-routine cognitive occupations. In fact, our results show that business and administration professionals as well as science and engineering associate professionals receive relatively higher rankings compared to teaching professionals, health associate professionals and personal service workers.

Ultimately, the overall impact of AI on the labour force will largely depend on the motivations for its deployment. If the main impetus is to cut labour costs, it might, similar to previous waves of automation, result in employment losses with minimal positive effects on productivity. Overall, there is room for public policy to shift incentives from a focus on machine intelligence to machine usefulness.

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Appendix 1

Table 4: ESCO Classification of Skills and Competences with Sub-categories.[7]

Domain	*Sub-category*	*Abbreviation*
Knowledge	Agriculture, forestry, fisheries and veterinary	K1
	Arts and humanities	K2
	Business, administration and law	K3
	Education	K4
	Engineering, manufacturing and construction	K5
	Generic programmes and qualifications	K6
	Health and welfare	K7
	Information and communications technologies	K8
	Natural sciences, mathematics and statistics	K9
	Services	K10
	Social sciences, journalism and information	K11
Skills	Communication, collaboration and creativity	S1
	Information skills	S2
	Assisting and caring	S3
	Management skills	S4
	Working with computers	S5
	Handling and moving	S6
	Constructing	S7
	Working with machinery and equipment	S8
Transversal skills and competences	Core skills and competencies	T1
	Thinking skills and competences	T2
	Self-management skills and competences	T3
	Social and communication skills and competences	T4
	Physical and manual skills and competences	T5
	Life skills and competences	T6

[7] Note that the ESCO classification contains an additional category for language skills. In our analysis these are subsumed under the 'Skills' category.

Table 5: ESCO Skill Categories with Sub-categories/tasks

Skill Category	*Sub-category / Task*
S1 – Communication, collaboration and creativity	S1.0 – Communication, collaboration and creativity
	S1.1 – Negotiating
	S1.2 – Liaising and networking
	S1.3 – Teaching and training
	S1.4 – Presenting information
	S1.5 – Advising and consulting
	S1.6 – Promoting, selling and purchasing
	S1.7 – Obtaining information verbally
	S1.8 – Working with others
	S1.9 – Solving problems
	S1.11 – Designing systems and products
	S1.12 – Creating artistic, visual or instructive materials
	S1.13 – Writing and composing
	S1.14 – Performing and entertaining
	S1.15 – Using more than one language
S2 – Information skills	S2.0 – Information skills
	S2.1 – Conducting studies, investigations and examinations
	S2.2 – Documenting and recording information
	S2.3 – Managing information
	S2.4 – Processing information
	S2.5 – Measuring physical properties
	S2.6 – Calculating and estimating
	S2.7 – Analysing and evaluating information and data
	S2.8 – Monitoring, inspecting and testing
	S2.9 – Monitoring developments in area of expertise
S3 – Assisting and caring	S3.0 – assisting and caring
	S3.1 – Counselling
	S3.2 – Providing health care or medical treatments
	S3.3 – Protecting and enforcing
	S3.4 – Providing information and support to the public and clients
	S3.5 – Preparing and serving food and drinks
	S3.6 – Providing general personal care

Table 2: ESCO Skill Categories with Sub-categories/tasks – Continued

S4 – Management skills	S4.0 – Management skills
	S4.1 – Developing objectives and strategies
	S4.2 – Organising, planning and scheduling work activities
	S4.3 – Allocating and controlling resources
	S4.4 – Performing administrative activities
	S4.5 – Leading and motivating
	S4.6 – Building and developing teams
	S4.7 – Recruiting and hiring
	S4.8 – Supervising people
	S4.9 – Making decisions
S5 – Working with computers	S5.0 – Working with computers
	S5.1 – Programming computer systems
	S5.2 – Setting up and protecting computer systems
	S5.5 – accessing and analysing digital data
	S5.6 – Using digital tools for collaboration, content creation and problem solving
	S5.7 – Using digital tools to control machinery
S6 – Handling and moving	S6.0 – Handling and moving
	S6.1 – Sorting and packaging goods and materials
	S6.2 – Moving and lifting
	S6.3 – Transforming and blending materials
	S6.4 – Tending plants and crops
	S6.5 – Assembling and fabricating products
	S6.6 – Making moulds, casts, models and patterns
	S6.7 – Using hand tools
	S6.9 – Handling animals
	S6.11 – Cleaning
	S6.12 – Washing and maintaining textiles and clothing
	S6.12 – Handling and disposing of waste and hazardous materials
S7 – Constructing	S7.0 – Constructing
	S7.1 – Building and repairing structures
	S7.2 – Installing interior or exterior infrastructure
	S7.3 – Finishing interior or exterior of structures

Table 2: ESCO Skill Categories with Sub-categories/tasks – Continued

S8 – Working with machinery and specialised equipment	S8.0 – Working with machinery and specialised equipment
	S8.1 – Operating mobile plant
	S8.2 – Driving vehicles
	S8.3 – Operating watercraft
	S8.4 – Operating machinery for the extraction and processing of raw materials
	S8.5 – Operating machinery for the manufacture of products
	S8.6 – Using precision instrumentation and equipment
	S8.7 – Installing, maintaining and repairing mechanical equipment
	S8.8 – Installing, maintaining and repairing electrical, electronic and precision equipment
	S8.9 – Operating aircraft

Table 6: ESCO Knowledge Domains with Sub-domains

Knowledge Domain	*Sub-Domain*
K1 – Agriculture, forestry, fisheries and veterinary	Agriculture
	Agriculture, forestry, fisheries and veterinary not elsewhere classified
	Agriculture, forestry, fisheries and veterinary not further defined
	Fisheries
	Forestry
	Inter-disciplinary programmes and qualifications involving agriculture, forestry, fisheries and veterinary
K2 – Arts and humanities	Arts
	Arts and humanities not elsewhere classified
	Arts and humanities not further defined
	Humanities (except languages)
	Inter-disciplinary programmes and qualifications involving arts and humanities
	Languages
K3 – Business, administration and law	Business and administration
	Business, administration and law not elsewhere specified
	Business, administration and law not further defined
	Inter-disciplinary programmes and qualifications involving business, administration and law
	Law
K4 – Education	Education
	Inter-disciplinary programmes and qualifications involving education
K5 – Engineering, manufacturing and construction	Architecture and construction
	Engineering and engineering trades
	Engineering, manufacturing and construction not further defined
	Inter-disciplinary programmes and qualifications involving engineering, manufacturing and construction
	Manufacturing and processing

Table 3: ESCO Knowledge Domains with Sub-domains - Continued

K6 – Generic programmes and qualifications	*Basic programmes and qualifications*
	Generic programmes and qualifications not elsewhere classified
	Generic programmes and qualifications not further defined
	Literacy and numeracy
	Personal skills and development
K7 – Health and welfare	Health
	Health and welfare not elsewhere classified
	Health and welfare not further defined
	Inter-disciplinary programmes and qualifications involving health and welfare
	Welfare
K8 – Information and communication technologies (icts)	Information and communication technologies (icts)
	Inter-disciplinary programmes and qualifications involving information and communications technologies (icts)
K9 – Natural sciences, mathematics and statistics	Biological and related sciences
	Environment
	Inter-disciplinary programmes and qualifications involving natural sciences, mathematics and statistics
	Mathematics and statistics
	Natural sciences, mathematics and statistics not elsewhere classified
	Natural sciences, mathematics and statistics not further defined
	Physical sciences
K10 - Services	Hygiene and occupational health services
	Inter-disciplinary programmes and qualifications involving services
	Personal services
	Security services
	Services not elsewhere classified
	Services not further defined
	Transport services

Table 3: ESCO Knowledge Domains with Sub-domains - Continued

K11 – Social Sciences, Journalism and Information	Inter-disciplinary programmes and qualifications involving social sciences, journalism and information
	Journalism and information
	Social and behavioural sciences
	Social sciences, journalism and information not further defined

Table 7: ESCO Transversal Skills and Competences with Sub-categories

T1 - Core skills and competences	*T1.1 - Mastering languages*
	T1.2 - Working with numbers and measures
	T1.3 - Working with digital devices and applications
T2 - Thinking skills and competences	T2.1 - Processing information, ideas and concepts
	T2.2 - Planning and organising
	T2.3 - Dealing with problems
	T2.4 - Thinking creatively and innovatively
T3 - Self-management skills and competences	T3.1 - Working efficiently
	T3.2 - Taking a proactive approach
	T3.3 - Maintaining a positive attitude
	T3.4 - Demonstrating willingness to learn
T4 - Social and communication skills and competences	T4.1 – Communicating
	T4.2 - Supporting others
	T4.3 - Collaborating in teams and networks
	T4.4 - Leading others
	T4.5 - Following ethical code of conduct
T5 - Physical and manual skills and competences	T5.1 - Manipulating and controlling objects and equipment
	T5.2 - Responding to physical circumstances
T6 - Life skills and competences	T6.1 - Applying health-related skills and competences
	T6.2 - Applying environmental skills and competences
	T6.3 - Applying civic skills and competences
	T6.4 - Applying cultural skills and competences
	T6.5 - Applying entrepreneurial and financial skills and competences
	T6.6 - Applying general knowledge

Appendix 2

The following Figures illustrate the mean rankings for the tasks related to the skill categories in ESCO.

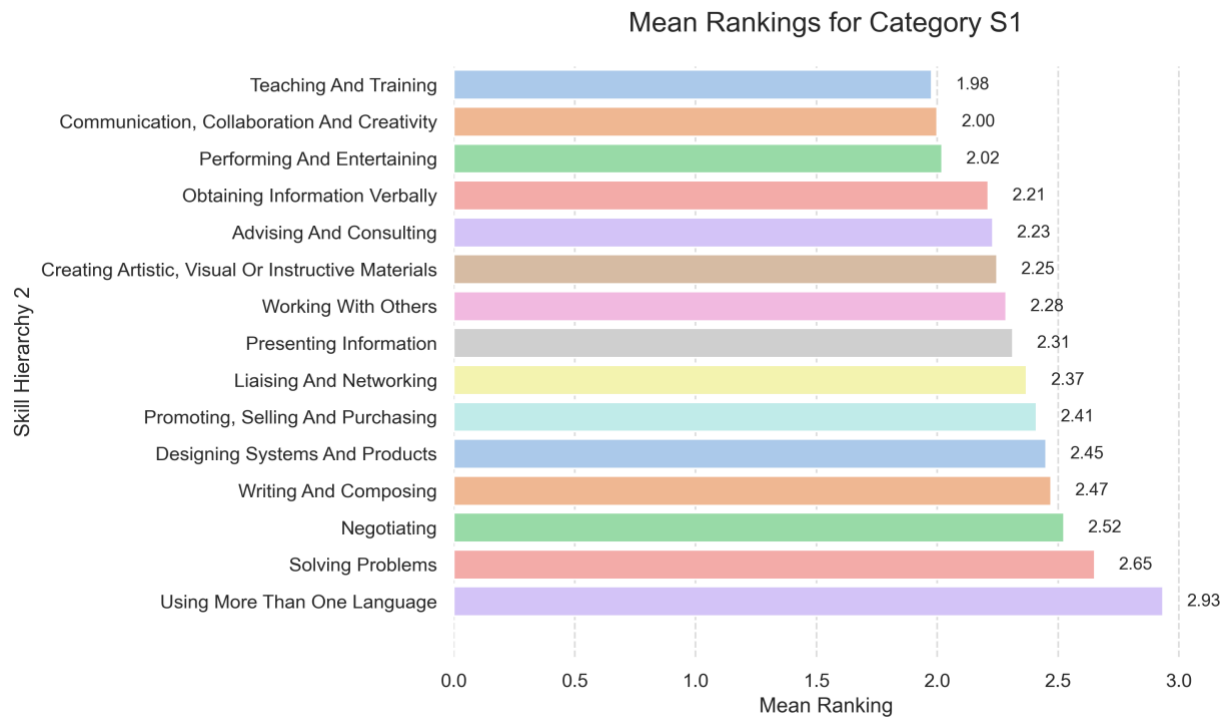

Figure 6: Mean Rankings for Tasks related to Skill Category S1 – Communication, Collaboration and Creativity.

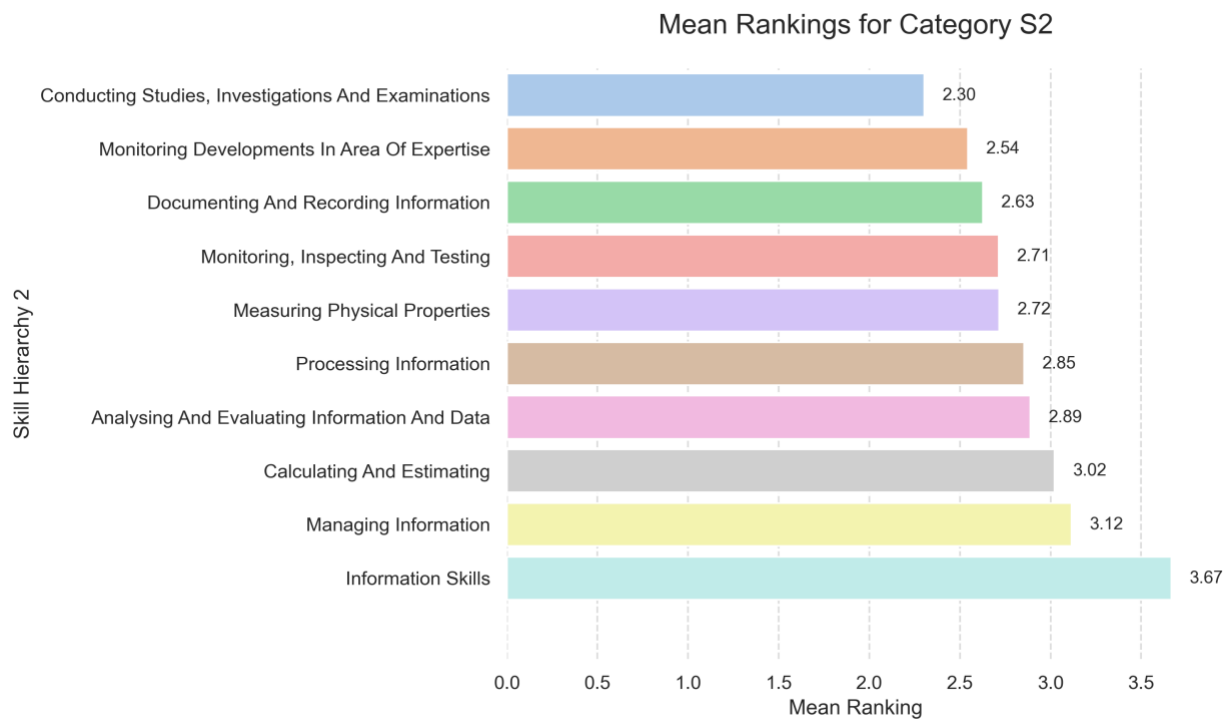

Figure 7: Mean Rankings for Tasks related to Skill Category S2 – Information Skills.

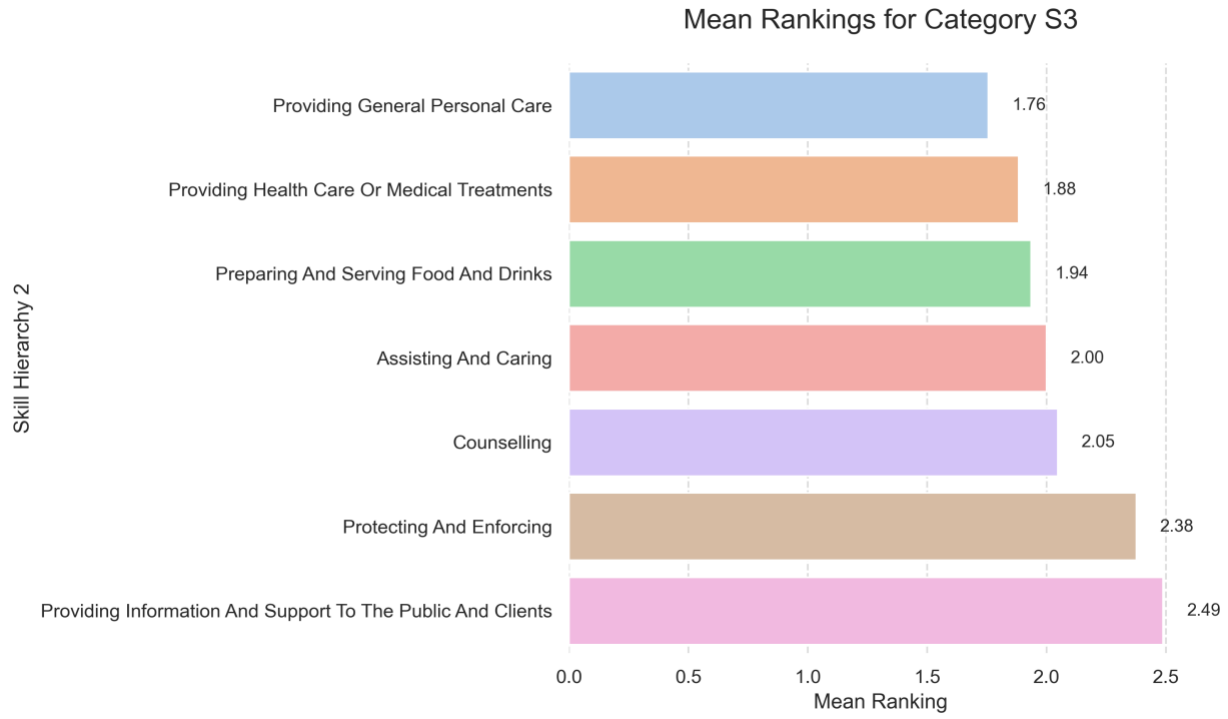

Figure 8: Mean Rankings for Tasks related to Skill Category S3 – Assisting and Caring.

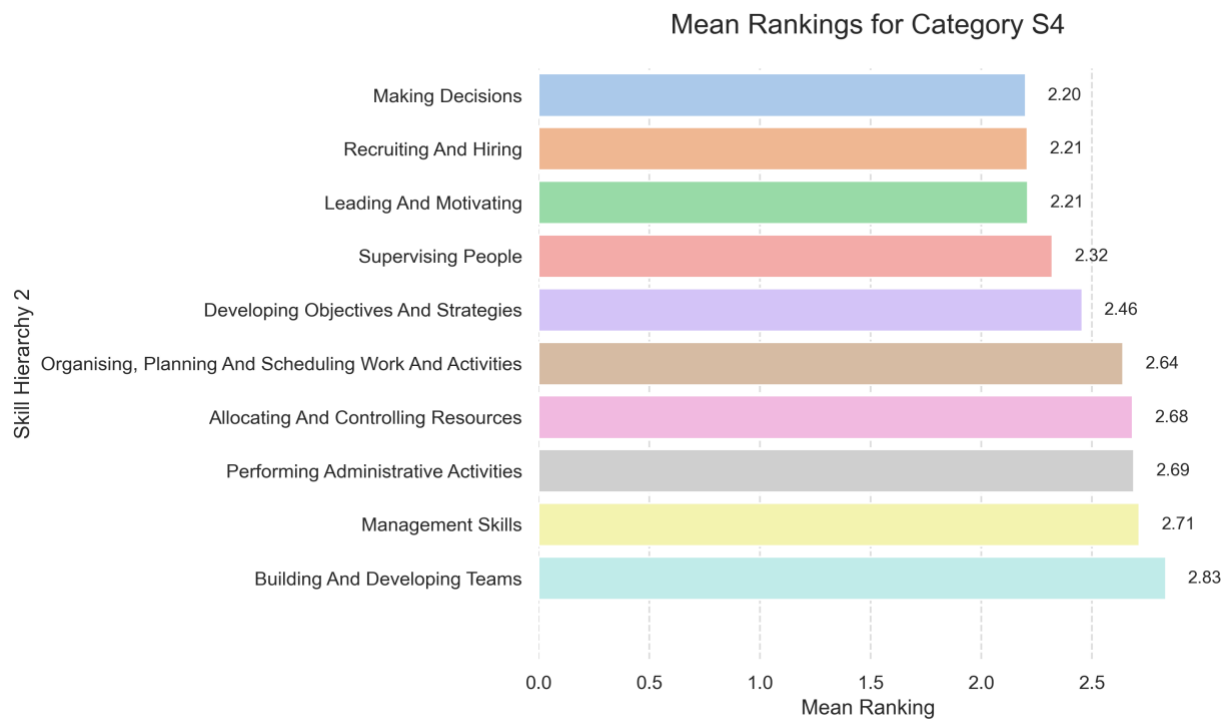

Figure 9: Mean Rankings for Tasks related to Skill Category S4 – Management Skills.

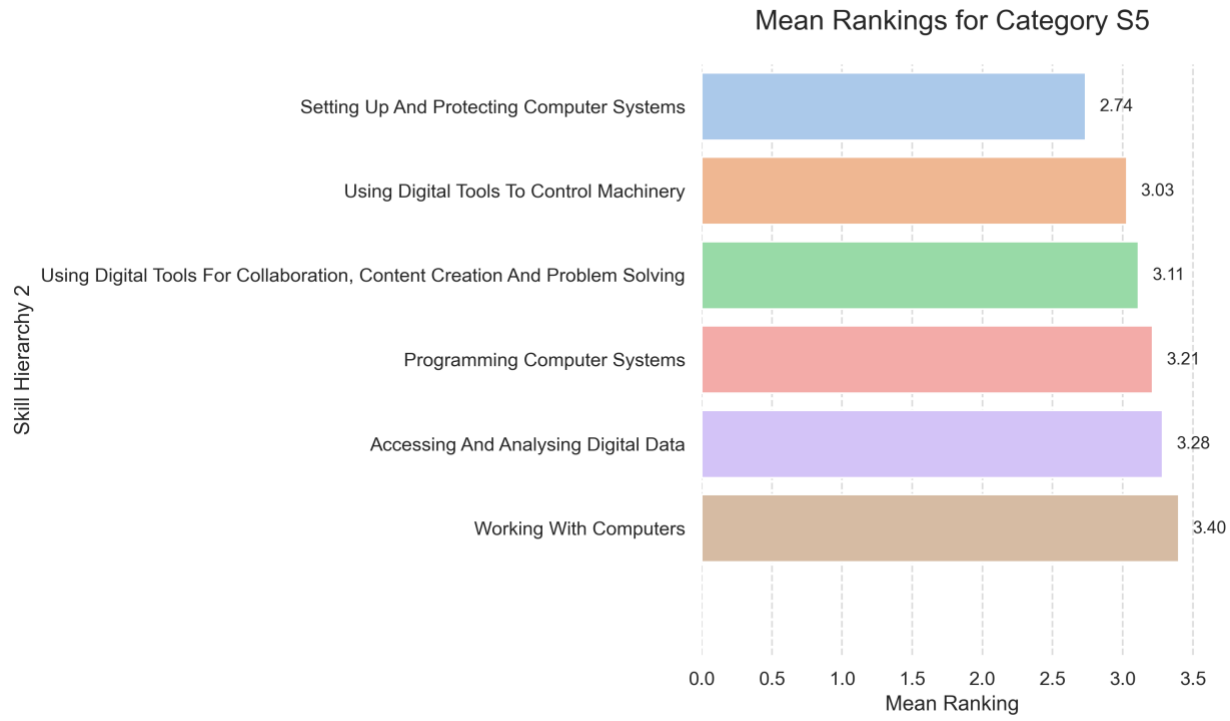

Figure 10: Mean Rankings for Tasks related to Skill Category S5 –Working with Computers.

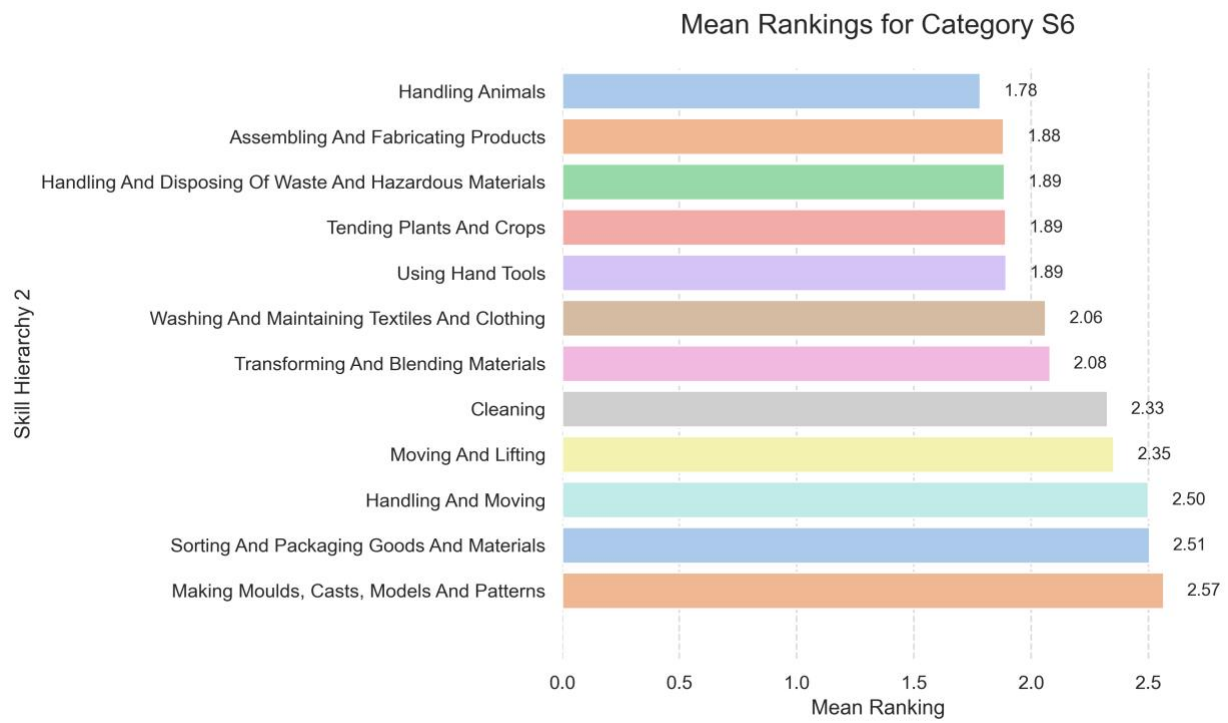

Figure 11: Mean Rankings for Tasks related to Skill Category S6 – Handling and Moving.

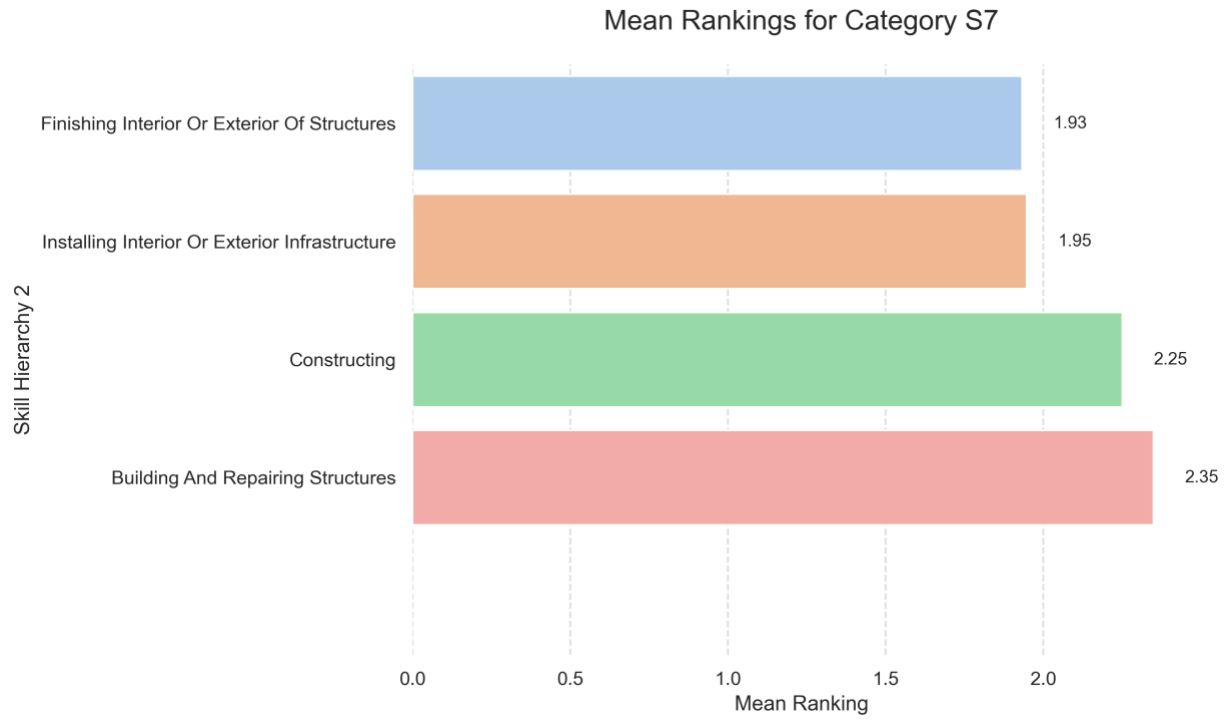

Figure 12: Mean Rankings for Tasks related to Skill Category S7 – Constructing.

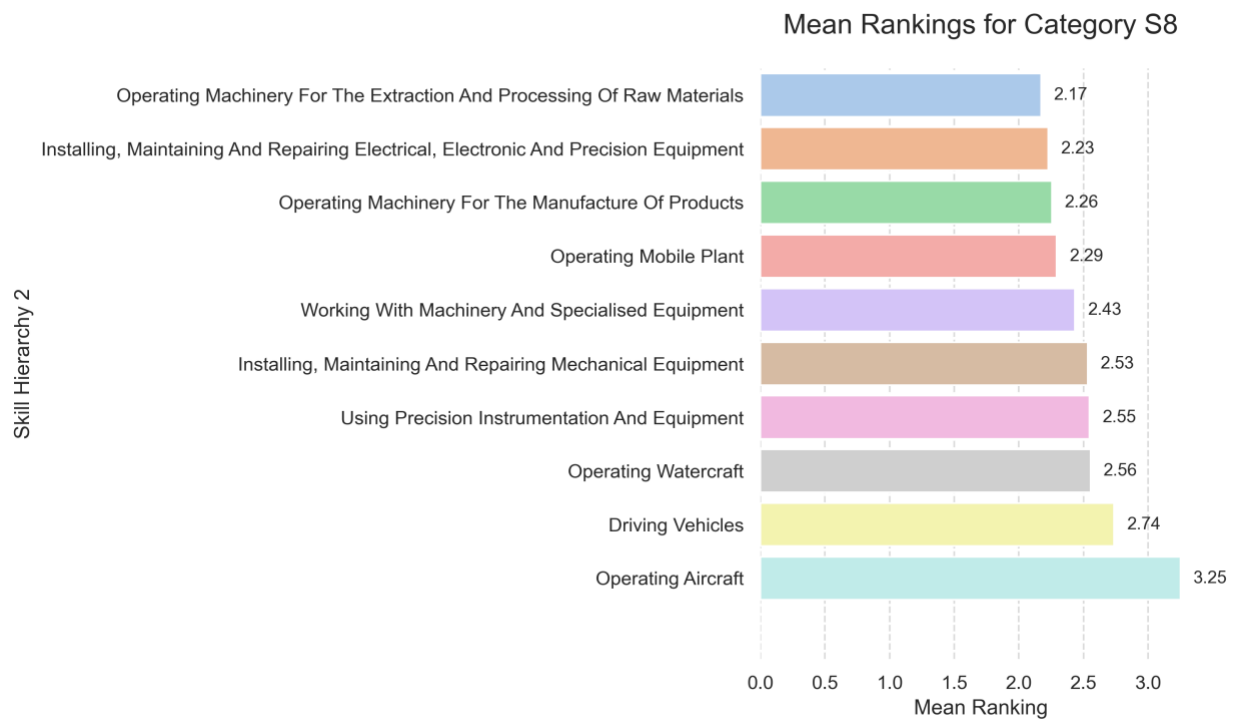

Figure 13: Mean Rankings for Tasks related to Skill Category S8 – Working with Machinery and Specialised Equipment.

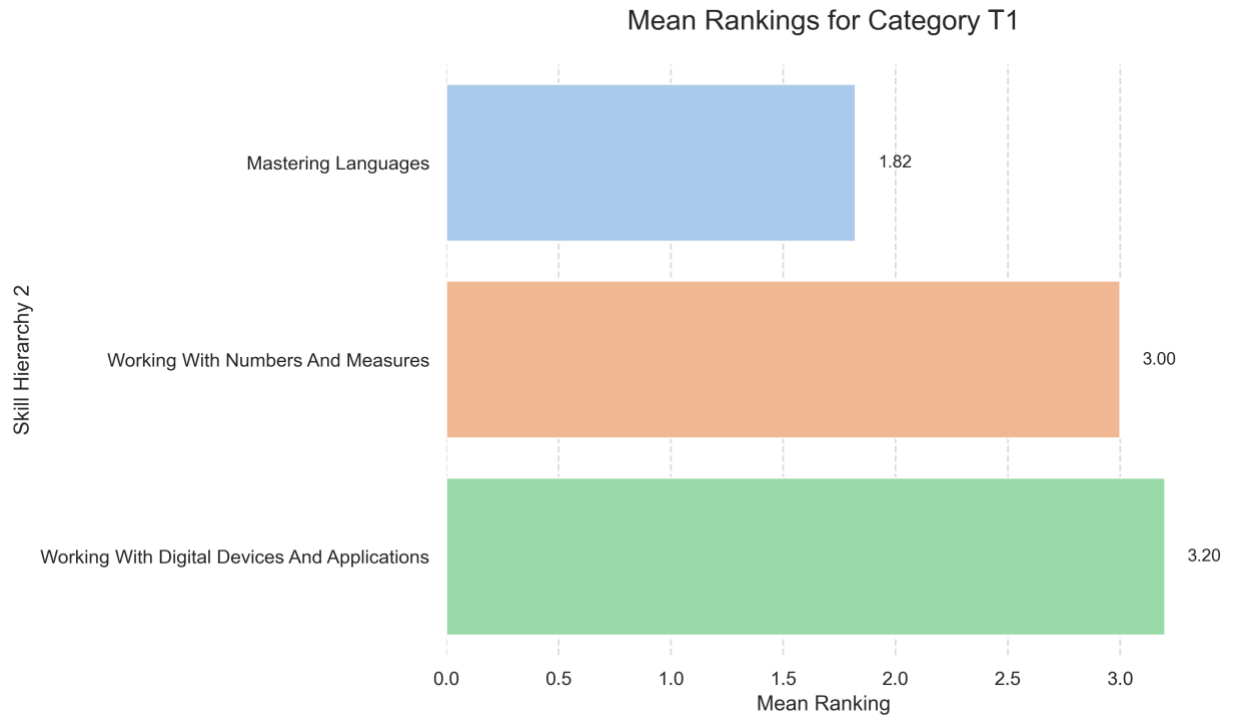

Figure 14: Mean Rankings for Tasks related to Skill Category T1 – Core Skills and Competences.

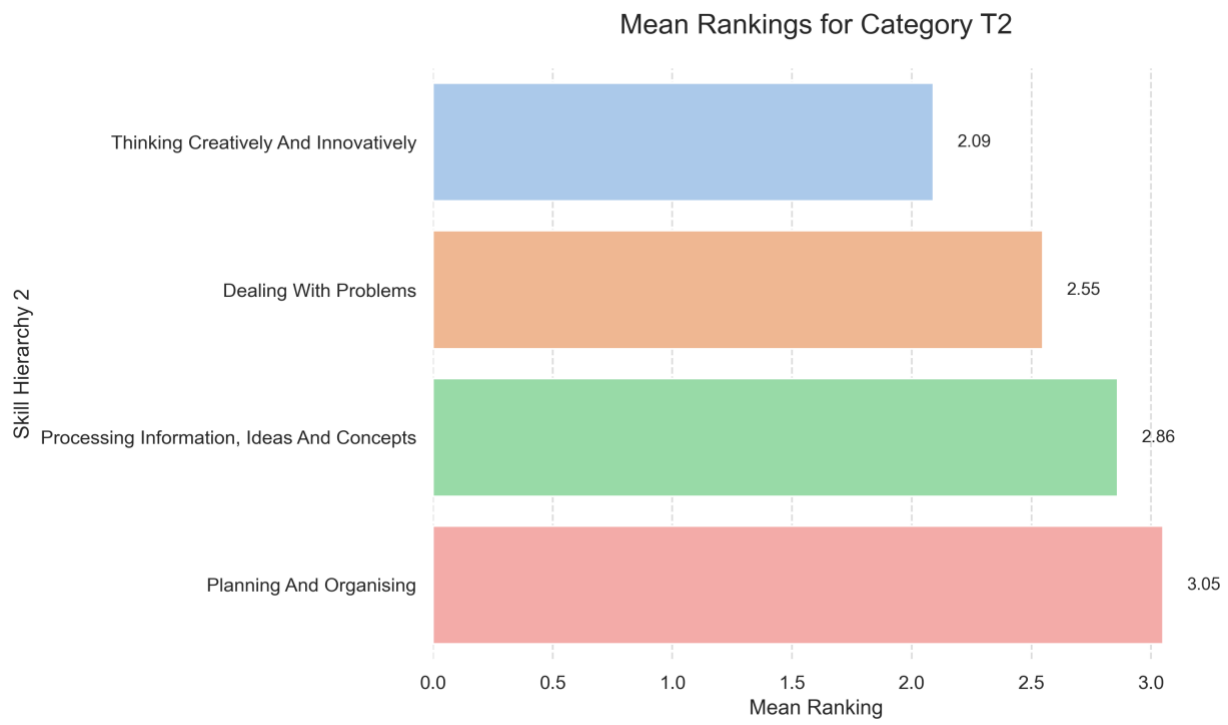

Figure 15: Mean Rankings for Tasks related to Skill Category T2 – Thinking Skills and Competences.

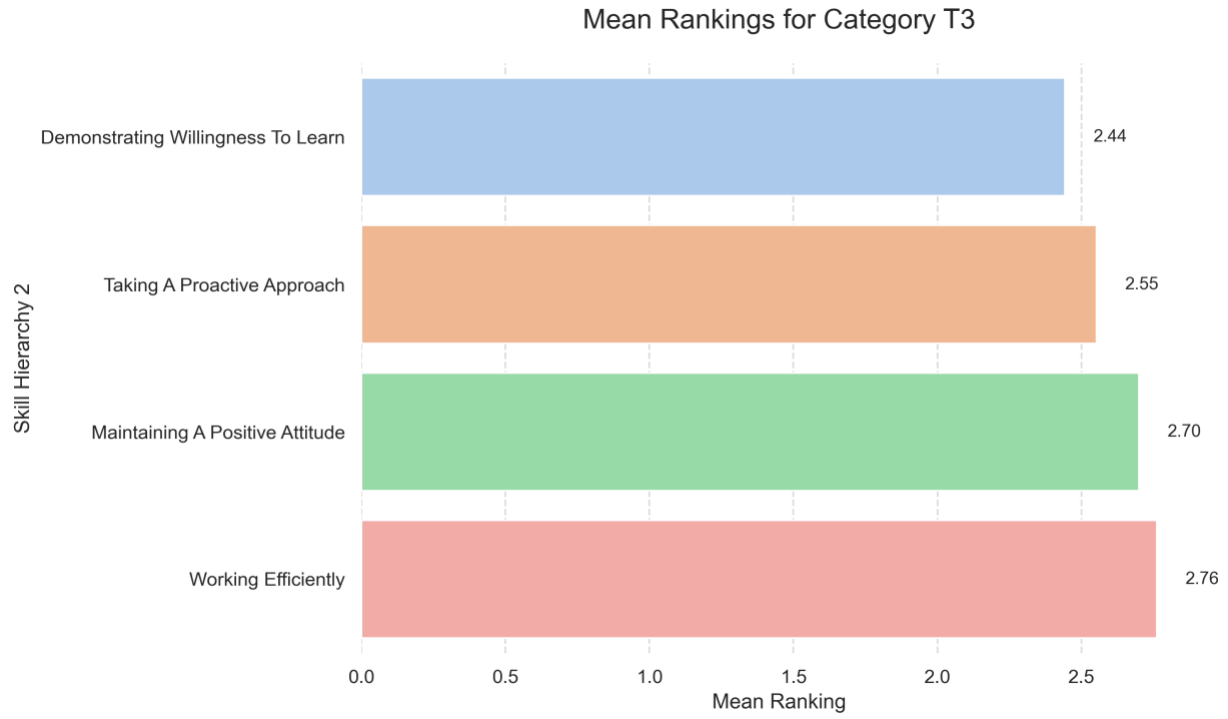

Figure 16: Mean Rankings for Tasks related to Skill Category T3 – Self-management Skills and Competences.

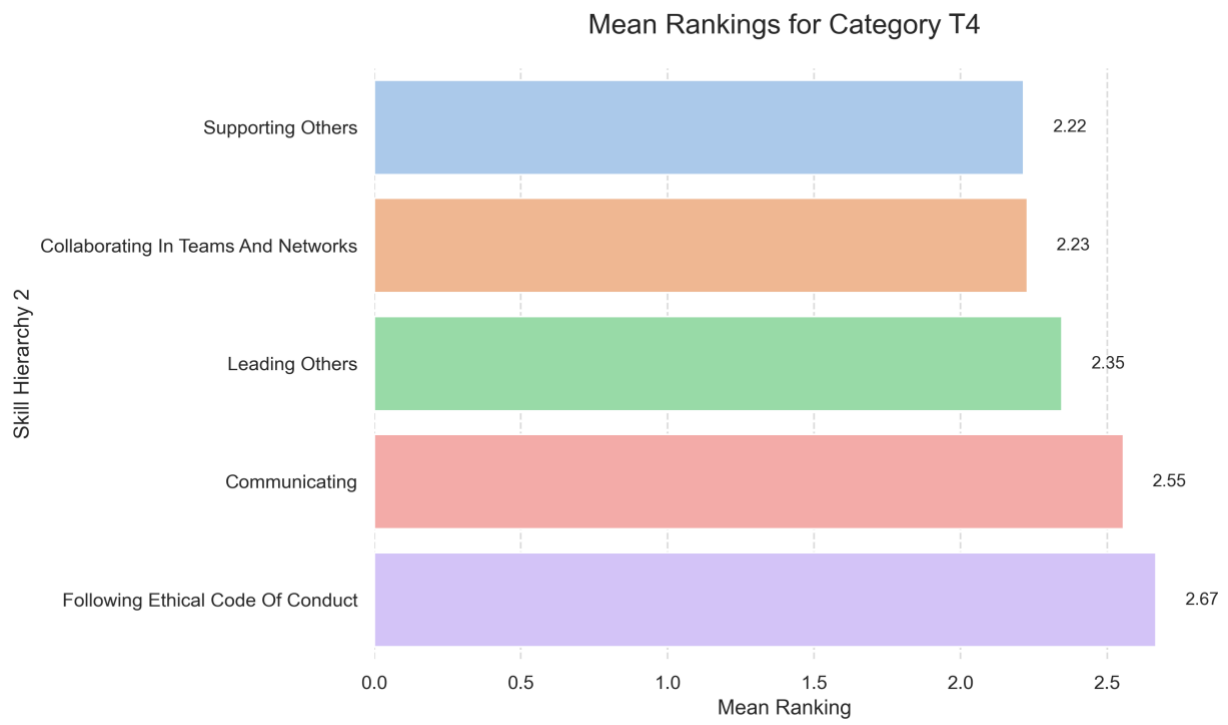

Figure 17: Mean Rankings for Tasks related to Skill Category T4 – Social and Communication Skills and Competences.

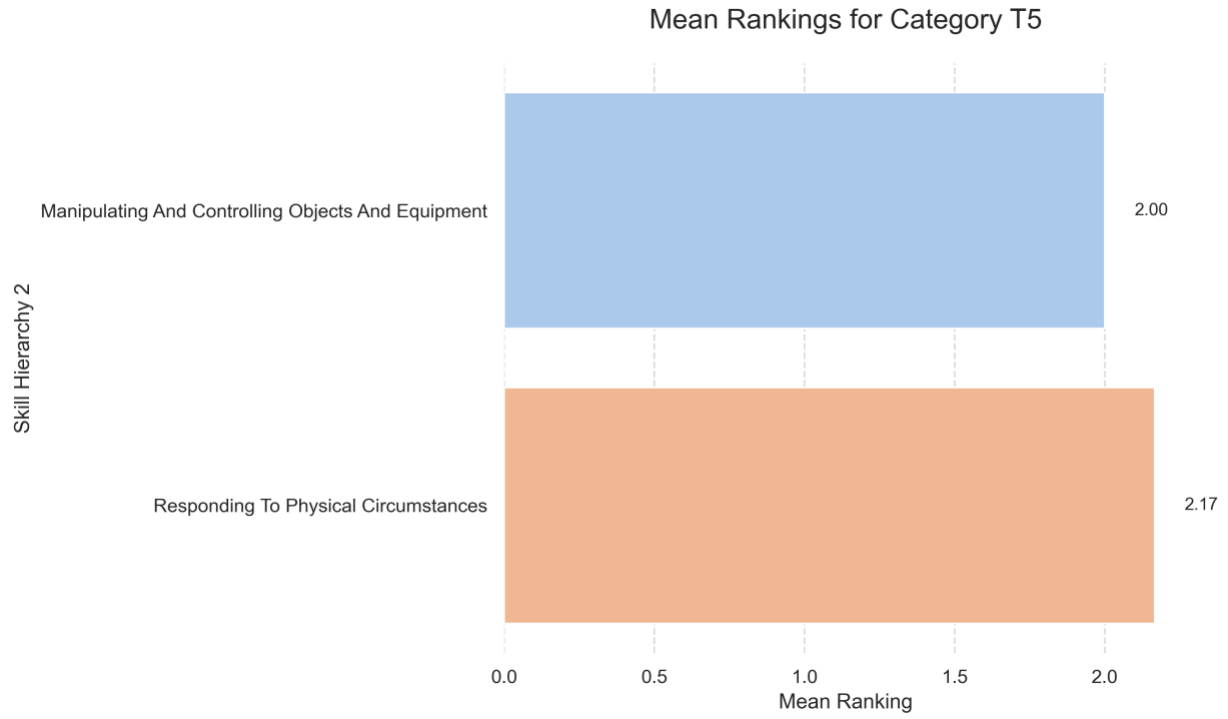

Figure 18: Mean Rankings for Tasks related to Skill Category T5 – Physical and Manual Skills and Competences.

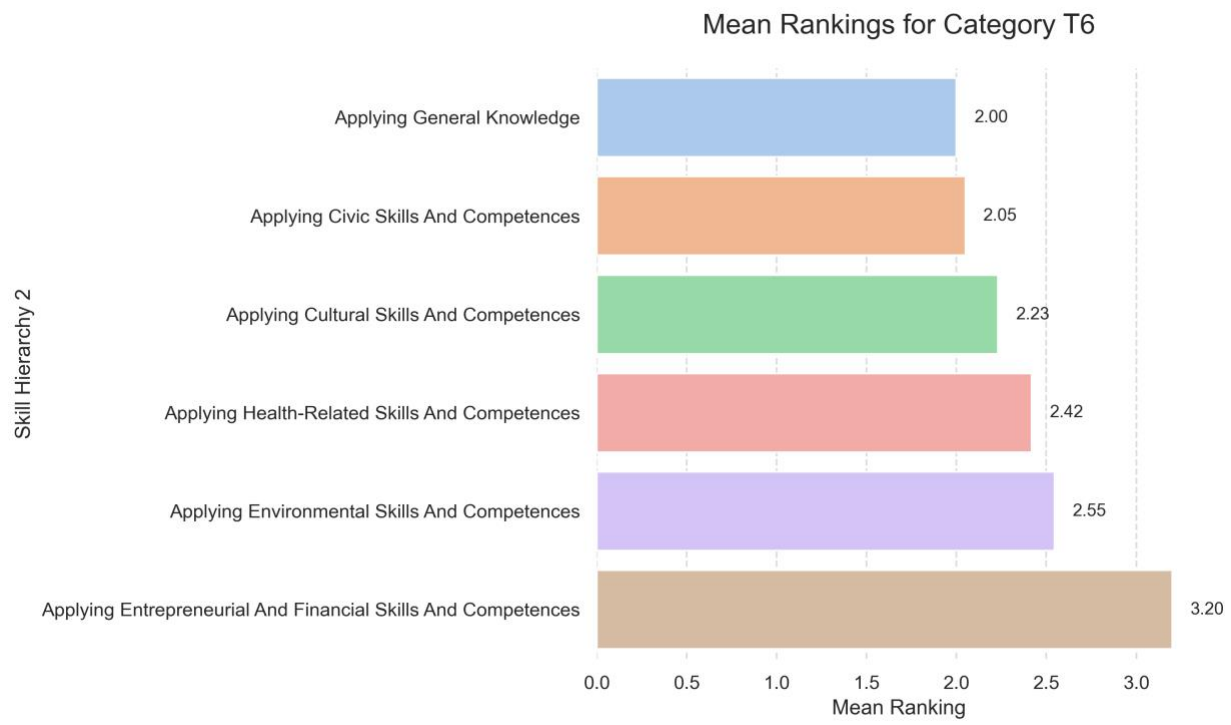

Figure 19: Mean Rankings for Tasks related to Skill Category T6 – Life Skills and Competences.

Appendix 3

Table 8: Top 10 occupations with highest average scores based on their essential skills and competencies.

Berufsbezeichnung	Occupation Name	Average Rating
CAD-Lederwaren-Schnitt-, Entwurfs- und Fertigungsmodelleur/CAD-Lederwaren-Schnitt-, Entwurfs- und Fertigungsdirektrice	Leather goods CAD patternmaker	4.20
Energieberater/Energieberaterin	Energy consultant	4.00
Datenbankadministrator/Datenbankadministratorin	Database administrator	3.81
Datenbankentwickler/Datenbankentwicklerin	Database developer	3.80
Steuerer Chemiewerksleitstand/Steuerin Chemiewerksleitstand	Chemical plant control room operator	3.77
Videotechniker/Videotechnikerin	Video technician	3.72
Entwickler von Benutzeroberflächen/Entwicklerin von Benutzeroberflächen	User interface developer	3.71
Rollenmaschinenarbeiter in der Kunststoffverarbeitung/ Rollenmaschinenarbeiterin in der Kunststoffverarbeitung	Plastic rolling machine operator	3.70
Hochschullehrkraft für Journalistik	Journalism lecturer	3.69
CAD-Fachkraft Bekleidung	Clothing CAD technician	3.68

Table 9: Top 10 occupations with lowest average scores based on essential skills and competencies.

Berufsbezeichnung	Occupation Name	Average Rating
Moderator/Moderatorin	Presenter	1.47
Farben- und Lacktechniker/Farben- und Lacktechnikerin	Lacquer maker	1.53
General/Generalin	Army general	1.54
Kabinenwart/Kabinenwartin	Locker room attendant	1.57
Asbestsanierer/Asbestsaniererin	Asbestos abatement worker	1.60
Schutzbekleidungshersteller/Schutzbekleidungsherstellerin	Protective clothing apparel manufacturer	1.60
Werbesachbearbeiter/Werbesachbearbeiterin	Advertising assistant	1.60
Seifenpresser/Seifenpresserin	Plodder operator	1.60
Wartelistenkoordinator/Wartelistenkoordinatorin	Waiting list coordinator	1.63
Arzt für Allgemeinmedizin/Ärztin für Allgemeinmedizin	General practitioner	1.66

Appendix 4

Table 10: Occupational Employment Share by 2-digit ISCO Code Germany, 2022 and Mean Rankings. Source: Eurostat, Employed persons by detailed occupation (ISCO-08 two digit level); Product Code: lfsa_egai2d.

ISCO	Berufsbezeichnung	Occupation	Employment Share (%)	Mean Ranking
OC33	Nicht akademische betriebswirtschaftliche und kaufmännische Fachkräfte und Verwaltungsfachkräfte	Business and administration associate professionals	7.06	2.68
OC41	Allgemeine Büro- und Sekretariatskräfte	General and keyboard clerks	6.61	3.09
OC32	Assistenzberufe im Gesundheitswesen	Health associate professionals	6.31	2.35
OC23	Lehrkräfte	Teaching professionals	5.91	2.39
OC52	Verkaufskräfte	Sales workers	5.88	2.81
OC72	Metallarbeiter, Mechaniker und verwandte Berufe	Metal, machinery and related trades workers	4.68	2.58
OC51	Berufe im Bereich personenbezogener Dienstleistungen	Personal service workers	4.47	2.32
OC31	Ingenieurtechnische und vergleichbare Fachkräfte	Science and engineering associate professionals	4.33	2.63
OC21	Naturwissenschaftler, Mathematiker und Ingenieure	Science and engineering professionals	4.27	2.55
OC24	Betriebswirte und vergleichbare akademische Berufe	Business and administration professionals	4	2.68
OC43	Bürokräfte im Finanz- und Rechnungswesen, in der Statistik und in der Materialwirtschaft	Numerical and material recording clerks	3.98	2.77
OC26	Juristen, Sozialwissenschaftler und Kulturberufe	Legal, social and cultural professionals	3.28	2.23
OC93	Hilfsarbeiter im Bergbau, im Bau, bei der Herstellung von Waren und im Transportwesen	Labourers in mining, construction, manufacturing and transport	2.9	2.55
OC91	Reinigungspersonal und Hilfskräfte	Cleaners and helpers	2.85	2.32
OC83	Fahrzeugführer und Bediener mobiler Anlagen	Drivers and mobile plant operators	2.83	2.54
OC71	Bau- und Ausbaufachkräfte sowie verwandte Berufe, ausgenommen Elektriker	Building and related trades workers, excluding electricians	2.61	2.21
OC25	Akademische und vergleichbare Fachkräfte in der Informations- und Kommunikationstechnologie	Information and communications technology professionals	2.44	3.00
OC81	Bediener stationärer Anlagen und Maschinen	Stationary plant and machine operators	2.44	2.49
OC22	Akademische und verwandte Gesundheitsberufe	Health professionals	2.31	2.25
OC53	Betreuungsberufe	Personal care workers	1.79	2.18
OC74	Elektriker- und Elektroniker	Electrical and electronic trades workers	1.78	2.41
OC75	Berufe in der Nahrungsmittelverarbeitung, Holzverarbeitung und Bekleidungsherstellung und verwandte handwerkliche Fachkräfte	Food processing, wood working, garment and other craft and related trades workers	1.6	2.38
OC42	Bürokräfte mit Kundenkontakt	Customer services clerks	1.52	2.75

OC34	Nicht akademische juristische, sozialpflegerische, kulturelle und verwandte Fachkräfte	Legal, social, cultural and related associate professionals		1.39	2.33
OC11	Geschäftsführer, Vorstände, leitende Verwaltungsbedienstete und Angehörige gesetzgebender Körperschaften	Chief executives, senior officials and legislators		1.27	2.41
OC54	Schutzkräfte und Sicherheitsbedienstete	Protective services workers		1.25	2.25
OC61	Fachkräfte in der Landwirtschaft	Market-oriented skilled agricultural workers		1.2	2.02
OC13	Führungskräfte in der Produktion und bei speziellen Dienstleistungen	Production and specialised services managers		1.18	2.67
OC12	Führungskräfte im kaufmännischen Bereich	Administrative and commercial managers		1.09	2.67
OC44	Sonstige Bürokräfte und verwandte Berufe	Other clerical support workers		1.07	2.76
OC35	Informations- und Kommunikationstechniker	Information and communications technicians		0.88	2.68
OC82	Montageberufe	Assemblers		0.87	2.53
OC94	Hilfskräfte in der Nahrungsmittelzubereitung	Food preparation assistants		0.77	2.54
OC96	Abfallentsorgungsarbeiter und sonstige Hilfsarbeitskräfte	Refuse workers and other elementary workers		0.55	2.46
OC73	Präzisionshandwerker, Drucker und kunsthandwerkliche Berufe	Handicraft and printing workers		0.53	2.26
OC14	Führungskräfte in Hotels und Restaurants, im Handel und in der Erbringung sonstiger Dienstleistungen	Hospitality, retail and other services managers		0.52	2.65
OC92	Hilfsarbeiter in der Land- und Forstwirtschaft und Fischerei	Agricultural, forestry and fishery labourers		0.31	1.99
OC62	Fachkräfte in Forstwirtschaft, Fischerei und Jagd ‚Äî Marktproduktion	Market-oriented skilled forestry, fishery and hunting workers		0.06	2.30
OC95	Straßenhändler und auf der Straße arbeitende Dienstleistungskräfte	Street and related sales and service workers	N/A		2.57