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Master Thesis

Artificial Intelligence and Employment in Germany:

A Task-Based Analysis of Exposure, Substitution, and Complementarity

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Abstract

The rapid diffusion of artificial intelligence (AI), especially following recent advances in large language models, has raised concerns about job displacement as well as hopes for productivity-driven growth. This thesis investigates how AI affects employment in the German labor market by focusing on tasks rather than occupations as a whole. Building on the task-based framework by Acemoglu and Restrepo (2022), AI exposure is separated into three dimensions: overall exposure, substitution potential, and complementarity potential.

Using the German Classification of Occupations (KldB 2010, revised 2020), all officially defined tasks are systematically collected and assessed with respect to their interaction with AI. These task-level evaluations are aggregated to the job level and linked to employment data to analyze differences across occupations and skill levels. The empirical analysis combines descriptive evidence with inferential statistics and regression models.

The results reveal strong heterogeneity in how jobs are affected by AI. Higher-skilled jobs tend to be more exposed to AI overall, while lower-skilled jobs face greater risks of task substitution. In contrast, AI complementarity is more prevalent among higher-skilled jobs. Employment outcomes reflect these patterns: the established substitution score is associated with negative employment effects, whereas high AI exposure in general is linked to employment gains. Taken together, the findings suggest that AI is currently reshaping jobs through changing tasks within jobs rather than leading to uniform job losses, underlining the importance of task-based approaches when assessing the labor market effects of AI.

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Abbreviations

AI – Artificial Intelligence

AIC – Akaike Information Criterion

e.g. – for example

Gen AI – Generative Artificial intelligence

GPT – General Purpose Technology

KldB 2010 – Classification of Occupations 2010 – revised version 2020

LLM – Large Language Model

n. P. – no page

SBTC – skill-biased technological change

1 Introduction

Artificial intelligence (AI) has emerged as one of the most consequential technological innovations of the 21st century. Following the rapid diffusion of large language models (LLMs) like ChatGPT in late 2022, AI systems have demonstrated an unprecedented ability to perform and augment a wide range of cognitive tasks, including text generation, data analysis, programming, and decision support (Korinek & Suh, 2024; Lane & Saint-Martin, 2021; Lorenz et al., 2023). As a result, concerns about the implications of AI for labor markets have intensified, with public discourse divided between fears of widespread job displacement and optimism about productivity-driven growth (Gries & Naudé, 2018; Maslej et al., 2025; Naudé, 2019). It is true that AI could lead the next industrial revolution and reshape labor markets entirely. But as with previous technologies, questions of job displacement and employment adaptation are to be answered, as well as overall impacts to be assessed. With almost 50% of workers already using AI at their workplace (Hartley et al., 2025, 3), researchers discuss sectors, occupations and jobs, that are exposed to AI, jobs that might become obsolete entirely or experience productivity gains through AI complementarity (Eloundou et al., 2024; E. Felten et al., 2021). Questions asked are: Who is to benefit and who is to lose out? How do education and skill interplay in these effects? And are any effects already observable today?

As AI is a fairly new technology, research is still limited and impact estimates uncertain. Nevertheless, some disruptions on the US labor market have already been reported (e.g. Chandar, 2025; Johnston & Makridis, 2025; Teutloff et al., 2025). Overall research suggests highly heterogeneous effects of AI on occupations and especially the tasks performed within jobs (D. Autor & Thompson, 2025). Due to AI's reliance on codifiable knowledge, clear outcome metrics, and large amounts of digital data, tasks such as text processing, data analysis, programming, and pattern recognition are most exposed (Acemoglu et al., 2022). Consequently, studies consistently find higher levels of AI exposure in predominantly cognitive working "white-collar" occupations, including business administration, legal professions and information technology, while manual and physical "blue-collar" occupations tend to be less exposed (Georgieff, 2024; OECD, 2025). Importantly, exposure does not necessarily imply substitution. Many highly exposed occupations appear to benefit from AI primarily through task augmentation and productivity gains stemming from complementarity rather than direct automation (Acemoglu & Restrepo, 2018b).

Evidence on economic outcomes, however, remains mixed. An increasing amount of studies report substantial productivity gains from AI adoption, due to faster and more accurate task completion allowing for time reallocation to more valuable tasks (Jaffe et al., 2024; Tomlinson et al., 2025). These productivity gains vary across occupations, tasks, and worker characteristics. While some findings suggest that lower-performing or less-experienced workers benefit more from AI support, thus closing the gap (e.g. Noy & Zhang, 2023), others point to stronger gains for highly skilled workers who are better able to leverage the technology (e.g. Van der Velde, 2020). Consequently, evidence on employment change is similarly ambiguous. Some studies report employment declines or reducing labor demand for tasks that are easily automated (e.g. Dominski & Lee, 2025), whereas others find neutral or even positive employment effects in jobs where AI complements human labor (e.g. Johnston & Makridis, 2025). Overall, there is no clear consensus yet on whether AI will primarily act as a labor-substituting or labor-complementing technology at the aggregate level. Additionally, it is difficult to distinguish between AI and other technologically driven employment change. As a result, it remains unclear how AI affects employment outcomes across jobs with different task compositions and skill requirements, and whether these effects are already observable.

Despite the growing body of literature, several important gaps remain. First, most studies do not account for the task composition of specific jobs but rather use occupation-level exposure. As a result, they are often unable to distinguish employment changes through task substitution, task complementarity or a combination of both. Second, the existing evidence is heavily biased regarding the American labor market, limiting external validity for other labor market contexts. Third, although some research has been conducted on skill-biased exposure effects of AI, these classifications have remained vague and are based solely on education, with a lack of official occupational classifications.

This thesis addresses these gaps by using a novel, task-based analysis of AI exposure and its labor market implications for Germany. For the first time, the full set of tasks defined in the *German Classification of Occupations*[1] (KldB 2010, revised version 2020) is systematically indexed and made available for research. Building on this task

[1] Original: Klassifikation der Berufe 2010, überarbeitete Version 2020.

inventory, each task is evaluated with respect to its exposure to AI, its potential for substitution by AI, and its potential for complementarity with AI. Aggregating these task-level measures to the job level allows for a differentiated assessment of how AI affects employment levels in all jobs of the German labor market.

To achieve this goal of closing some of the existing research gap, this thesis aims to answer the following research question: "*How does occupational exposure to Artificial Intelligence — measured through task-level exposure, substitution, and complementarity — affect employment outcomes across skill levels in the German labor market?*" A sub-question answered is: *How does skill level affect exposure to AI regarding task-level exposure, substitution and complementarity*?

The rest of the thesis is organized as follows. The next section will provide the necessary definitions needed for this analysis. Section three provides a theoretical background, starting with a historical outline, continuing with growth and AI before then elaborating on two main theories and establishing hypotheses. Section four will provide previous findings on occupations, skill and exposure. Section five then presents previous findings regarding AI and employment. Section six presents the method of the performed analysis. Results are presented in section seven and discussed in section 8. The thesis concludes in section nine.

2 Definitions

Before diving into the content of this thesis, it is important to define and explain certain terms that will be used throughout this work.[2] First and most importantly is the term *Artificial Intelligence* (AI). There are many definitions floating around to define AI and its nature (Wang, 2019). A commonly used definition was published by the OECD defining an AI system as a "machine-based system, that for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations or decisions" (OECD, 2024, p. 4). Simply put, an AI is given objectives to achieve and is given inputs that it should work with, to achieve those objectives. Whether the AI managed to achieve these objectives is then ranked and fed back to the machine. This process is called training. After training, if an AI is presented with an input and an objective, it can use its own "learnings" to generate

[2] Readers that are well-versed in the field of economics and artificial intelligence may wish to skip this section.

outputs. Important for this work, is the additional definition of *Generative Artificial Intelligence* (Gen AI), that will be used in a similar way to AI in the later analysis of this thesis. Gen AI „refers to computational techniques that are capable of generating seemingly new, meaningful content such as texts, images, or audio from training data" (Feuerriegel et al., 2024, p. 2). Most of the times, Gen AIs are so-called *Large Language Models* (LLMs), that **"**work by predicting the probabilities of [the] next word (token), given an input string of text, based on the statistical properties of the language in the training data" (New York University, 2025). Thus, inputs can be wrong or misleading. To effectively use GenAI and LLMs, the user's inputs given to the AI are called *prompts*, which are "natural language quer[ies] to a foundation model, which typically are large language models like GPT-4 made by OpenAI*"* (Liang et al., 2024, p. 2). Prompts are the input an AI uses to process and generate an output.

Now, for the economic analysis, some terms need to be defined. First, an *occupation* is a "work or profession that an individual engages in to earn a living" (DocMcKee Sociology Glossary, 2024). In this work, the words occupation and job will not be used synonymously, as *job* refers to an occupation being performed at a certain skill level. As an example take carpenters: This occupation can be performed by any worker at a helper level but requires high skill at a professional industry standard, therefore this occupation has multiple jobs under its name. In this work, all jobs will be made up of individual arrays of *tasks*. Tasks are defined as "piece[s] of work assigned or done as part of one's duties" (The American Heritage Dictionary, 2025). To perform a task in a job, workers need *skills*. A skill is defined as the "ability to apply knowledge and use know-how to complete tasks and solve problems" (European Union, p. 227).

3 Theory

3.1 Historical development

To understand how AI may affect labor and employment levels, this thesis starts with a brief section on historical development and how previous waves of technological advancements have shaped the labor market.

There have always been technological advancements in market economies to help achieve more productivity, save cost and arguably provide prosperity for all. Beginning with the invention of the wheel, new metals like bronze and iron, the invention of the printing press or the steam engine. All these technologies are considered general

purpose technologies (GPTs), which describe a new method of producing and inventing that is important enough to have a long-lasting aggregate impact (Jovanovic & Rousseau, 2005). GPTs act as „innovational complementarities“, where advancements in GPTs boost Research of their own development (Bresnahan & Trajtenberg, 1992, p. 2). These advancements can afterwards be applied in downstream technologies. Later GPTs include electricity, computers and robots, with Artificial intelligence (AI) arguably being the next GPT on the horizon (Bresnahan & Trajtenberg, 1992, pp. 1–2). All these technological advancements have brought productivity gains through automation of tasks, that previously were performed by humans. When looking back to the second industrial revolution, carriages were replaced by railroads, sailboats by steamboats, dock workers by cranes, etc.. A clear substitution effect among workers was evident (Acemoglu & Restrepo, 2018c, p. 1489). On the other hand, it created the need for engineers, repairmen and machinists, shifting demand and creating new jobs. When analyzing more recent developments in technology, robotization and computerization come to mind. Robots are seen primarily replacing manual labor and “blue-collar” jobs like machinists and welders, while not providing an opportunity for all displaced workers to shift to other fields (Acemoglu & Restrepo, 2020a, p. 2233). That is why, Acemoglu and Restrepo (2020a, p. 2192) find each robot introduced in a community leads to a reduced employment-population ratio by 0.2 percentage points and wage declines in the area by 0.42%. This rise in robotic automation and its impacts are thought to be different for skill groups, replacing manual routine tasks, diminishing labor demand and favoring skilled workers (D. H. Autor et al., 2003). This has led to an increase in earnings inequality in the US since the 1970s and the introduction of the term “skill-biased technological change”, which is explained in section 3.2.3 (Grant & Üngör, 2024, p. 748). The increase in wage gap has historically been observed by many scholars from the 1970s onwards and been directly connected to automation and substitution, with between 50 and 70% of wage decline being directly explainable by automation through substitution (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2022, p. 2013).

However, in the last decade, since 2015, the labor market has seen a stabilization in the wage gap for the first time in 40 years (Aeppli & Wilmers, 2022; Dey et al., 2018), which could indicate more equally distributed exposure to automation and substitution or improved alternatives for low-skilled workers. Some argue, that routine manual

tasks, have now been automated to a degree, where it becomes feasible to develop technology, that automates other non-routine work that has seen demand increase in the last decades (Bloom et al., 2025, p. 2; Webb, 2019). One of these technologies could be AI, which, some argue, could affect highly skilled workers performing non-routine cognitive tasks, previously deemed "unautomatable" (Georgieff, 2024, p. 12). Thus, automating tasks like language translation, text generation, coding and overall problem-solving could reshape the labor market rapidly and extensively (Ellingrud et al., 2023). Therefore, AI could be different from all previous waves of automation, as it could target "white collar" jobs rather than manual labor "blue collar" jobs (Chen et al., 2025, p. 5). Due to research on this topic still being very limited, there are numerous differing predictions on future developments with some arguing, that eventually, old patterns will repeat, and low skilled workers will once again be most affected and substituted (e.g. Dauth et al., 2021), whilst others predict disruptions in the labor market, with highly skilled workers being exposed and most affected (e.g. Webb, 2019). Some argue that it remains unclear how different elasticities affect the substitution between capital and labor with varying skill levels, as well as other demographic factors, making it difficult to make a clear prediction. (Krusell et al., 2000, p. 1030).

3.2 Growth through automation and AI

There are a lot of theories at play, when considering the impact of AI on employment. There are growth theory, labor demand theory, coupling of wages and productivity and theory of skill-biased technological change. All of these are presented briefly in this section.

3.2.1 AI induced growth and changes in labor demand

As AI is seen as a productivity improving technology, it naturally leads to growth across the economy. Lane and Saint-Martin (2021, p. 29) argue, this growth will take an "S-shape pattern" with slow but accelerating growth due to lacking implementation at the beginning, but with substantial growth once AI has made its way into many forms of production. Throughout this time, AI will improve through competition and complementary technologies it brings upon as a general purpose technology. When aggregating their found individual productivity gains Maslej et al. (2025, p. 268) estimate AI induced growth of 10-45% p.a. in the first years; however, given the methodology used to derive these figures, they should be interpreted with caution. Acemoglu (2024, p. 34) provides more modest growth estimates ranging from 0.66% to 1.16% in

the upcoming ten years in total due to AI and estimates a rise in GDP based on AI-induced productivity gains will be around 1% in the upcoming ten years. Aghion et al. (2017, pp. 6–7) add a constraint on AI induced growth due to an effect similar to Baumol's cost disease[3], limiting productivity improvements in areas hard to automate or improve. All these predictions are made under the assumption, that AI is an automation technology and is merely substituting for labor. But as presented above, some scholars argue, AI might not be like previous automation technologies and therefore have other effects (Naudé, 2019, p. 2). As an example, Acemoglu (2024, p. 4) argues, that AI can foster growth in more ways than just automation, but rather through complementarity, deepening of automation and new tasks becoming available. All of which will be explained with regards to his task-based framework in section 3.3.1.

What effects AI induced growth will have on labor is difficult to predict, as lower costs or improved productivity by theory lead to increased output, fostering demand for products and in turn increasing labor demand. However, if AI primarily substitutes for labor as an automation technology, displacement can dominate, reducing labor demand despite higher aggregate output.

3.2.2 Coupling of productivity and wage / employment

In standard labor market theory, wages are closely linked to labor productivity. Under competitive conditions, companies employ workers up to the point where the real wage equals the worker's marginal product of labor (Ehrenberg et al., 2023, p. 357). As a result, productivity-enhancing technological change is expected to raise wages and labor demand, provided that output prices and labor market institutions do not offset these effects (Acemoglu & Autor, 2011; Solow, 1957). However, the strength of this coupling depends on how productivity gains are generated and distributed. When productivity gains arise from labor-augmenting technologies that complement workers, labor demand tends to rise, leading to higher wages and potentially higher employment. In contrast, when productivity gains stem from labor-saving automation that substitutes capital for labor, employment and wage growth may stagnate or decline despite rising output (Acemoglu & Restrepo, 2018a).

[3] Baumol's cost disease describes the tendency for wages and costs to rise in labor-intensive sectors with low productivity growth (e.g. education or health care) because they must keep pace with wage increases in high-productivity sectors, leading to rising relative prices despite little productivity improvement. Baumol and Bowen (1965).

3.2.3 Skill-biased technological change

Skill-biased technological change (SBTC) refers to technological progress that raises the relative demand for skilled workers by complementing their tasks and increasing their marginal productivity. In the canonical model, SBTC disproportionately benefits high-skilled labor, leading to a rising skill and college wage premium[4] despite increasing skill supply (Acemoglu & Autor, 2011, pp. 1097–1098). This theory successfully explains long-run increases in wage inequality driven by demand shifts toward educated workers.

However, Acemoglu and Autor (2011) emphasize that SBTC alone is insufficient to explain key empirical patterns such as declining real wages for low-skilled workers and employment polarization. They argue that a task-based interpretation is necessary, as technologies often substitute for labor in specific tasks rather than jobs as a whole. For this reason, they developed such a task-based model, that will be presented in 3.3.1. When considering AI as a skill-biased technology, shifts can occur regarding the benefiting group. Some argue, there are signs that low-skilled workers may benefit more. They proclaim, as AI is trained on high-quality examples, low-skilled workers may have more to gain from using it (Hoffmann et al., 2025, p. 16).

On the other hand, higher skilled workers are expected to more easily adapt and shift work to non-automatable areas like creative and social skills (Fossen & Sorgner, 2019, pp. 13–14). Additionally, they more easily learn new information, helping with lifelong learning (Lane & Saint-Martin, 2021, p. 35). Bartel and Lichtenberg (1987) argue, that highly educated workers are in general more prepared for dealing with changes in work environments.

How exactly all of these effects will interplay and result in employment differing outcomes is difficult to predict and observe. Nevertheless, there are two models trying to establish a foundation for any analysis in this area of research.

3.3 Models of technological advancement and its employment impacts

These two models of technology and labor have been regarded as the most compelling in explaining current trends in employment with regard to AI. They are: the task-based

[4] The college premium denotes the wage differential between college-educated and non-college-educated workers and is largely driven by relative supply and demand for skilled labor, particularly through skill-biased technological change that increases the productivity and wages of high-skilled workers (Krusell et al., 2000; Autor et al., 1997; Goldin & Katz, 2010). For more, see the appendix.

framework by Acemoglu and Restrepo (2022/2024) and the expertise model by D. Autor and Thompson (2025). These models and their implications are briefly presented in the next subsections. Additionally there is a model constructed by Bloom et al. (2025), that elaborates on the impact of AI on wage and the skill premium. This model is presented in the appendix, as mainly wage effects are derived from it, and employment effects are secondary.

3.3.1 Acemoglu & Restrepo (2022/2024) task-based framework

The task-based framework was first introduced by D. H. Autor et al. in 2003 with the novel idea of conceptualizing production as a set of tasks rather than broad occupations. This was used to show how computerization substituted workers, by substituting tasks and changing work dynamics. Building on this model, Acemoglu and Autor developed a formal general equilibrium model linking skills, tasks and technology in 2011. In this version of their model, they were able to incorporate skill-biased technological change based on tasks for the first time, in the sense, that technology might automate certain tasks based on skill but not an entire occupation. In 2018, Acemoglu and Restrepo further extended the framework to specifically explain how automation technology leads to displacement and reinstatement of workers, based on tasks as an interplay between capital and labor. Their goal was to determine changes in aggregate labor demand and the evolution of the labor share. In this framework, firms decide endogenously which tasks to automate, and for the first time in theory, technological progress could be both productivity-enhancing and labor-displacing (Acemoglu & Restrepo, 2018c, p. 1489). The latest iteration published by Acemoglu in 2024 is now explicitly aimed at explaining the impacts of AI with regards to the previous models. The following analysis will draw on this model to explain essential mechanisms of automation-based labor reallocation.[5]

The baseline assumption of this model and all analyses performed in this thesis is this: Occupations – distinguished into jobs by skill – and production are made up of several distinct tasks. In Acemoglu's model, these tasks line up on a continuum based on the difficulty of being automated. Each task can be performed either by capital or by labor, which each have comparative advantages (Acemoglu, 2024, p. 2; Acemoglu & Restrepo, 2018c, p. 1489). Whilst capital has a cost advantage for automatable tasks,

[5] This thesis relies on the static version of the model, although similar dynamic versions have since been published but did not yield differing results.

labor naturally always has a comparative advantage in new tasks (Acemoglu & Restrepo, 2018c). Acemoglu does not yet distinguish the types of labor into high or low skilled, a feature that might be of interest later.[6] Technology and innovation now impact this system through making more tasks accessible to automation.

This system is visualized in Figure 1, where all tasks z ∈ (0,N) are lined up on a continuum from 0 to N, and there exists a current level of technology I. In this case, all tasks z with z ≤ I are produced with capital and are automated, while all tasks z > I are produced using human labor (interval Ĩ), as no technology is available. Mathematically, Acemoglu expresses this as a two input production function with output y(z) for each task z:

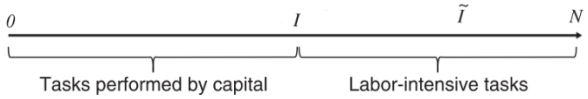


Figure 1: The task spectrum based on Acemoglu and Restrepo (2018c, p. 1497)

$$y(z) = A_L \gamma_L(z)[l(z)^{1-\kappa} k_C(z)^{\kappa}] + A_K \gamma_K(z) k(z)$$

where A_L and A_k are labor- and capital-augmenting productivity terms, $\gamma_L(z)$ and $\gamma_K(z)$ are labor's and capital's "task-specific productivity schedules". $l(z)$ and k(z) resemble labor and capital allocated to performing task z, with $k_C(z)$ being labor complementary capital like computer programs and machines requiring an operator. κ is the share of complementary capital in labor production. $\kappa < 1$ has to hold, in order for the task to require labor. Overall, this production function implies that capital and labor may have different productivities in different tasks but within tasks, they are perfect substitutes. As labor is assumed to have a comparative advantage to capital for higher indexed tasks, $\gamma_l(z)/\gamma_K(z)$ is increasing, such that there exists a threshold I, such that tasks z ≤ I are produced with capital and those with z > I are produced with labor. Acemoglu continues to include cost of labor and cost of capital in his model, but this will be excluded here, as it is not needed for the analysis.

Now, technological advancements, e.g. AI, can impact growth, productivity and employment in this model in 4 distinct ways:

[6] Further assumptions include fixed capital stock and exogenous technology. Acemoglu and Restrepo (2018c, p. 1490).

1. Automation: As technology and AI's capabilities increase (increase of I), automation takes over tasks previously performed by labor and therefore reduces costs. This can be seen in Figure 2. In this case, as I increases, the set of automated tasks expands, as tasks with $z \leq I$ are automated. This reduces cost, might increase output and definitely reduces employment. Additionally there will be negative effects on wages and the labor share according to Acemoglu and Restrepo (2018c, p. 1490). For the case of GenAI, tasks that are newly automated could be "clerical functions, text summary, data classification and pattern recognition" (Acemoglu, 2024, p. 4).

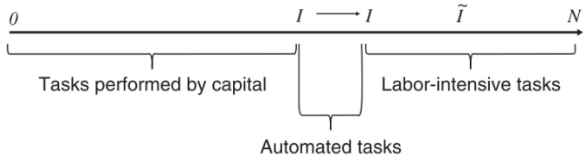


Figure 2: Innovation modeled in the task spectrum based on Acemoglu and Restrepo (2018c, p. 1497)

2. Task complementarity: Productivity in tasks can be increased by using technology and AI through complementary means, even raising the marginal product of labor. In the model, this can be represented as a reduction in cost for labor complementary capital $k_C(z)$ in some tasks $z > I$, reducing overall labor cost and improving output eventually leading to rising employment. Additionally, AI may automate some subtasks of z, that free up time and allow workers to specialize in remaining subtasks of $z > I$. This might have revolving effects of increased employment. To give an example, AI could provide basic information more easily or automate documenting subtasks (Acemoglu, 2024, p. 4).
3. Deepening of automation: Advancements in technology and AI could bring about improved performance of already existing capital, increasing $\gamma_K(z)$, thus increasing the capital share, reducing costs and possibly employment.
4. New technologies and AI can generate new labor-intensive products and tasks, which could be modelled as an increase in N (Acemoglu, 2024, pp. 4–5). There are many ways this could happen, either by directly being enabled through new technologies or by spillovers into other industries.[7] When N increases, the set of overall tasks either expands or shifts

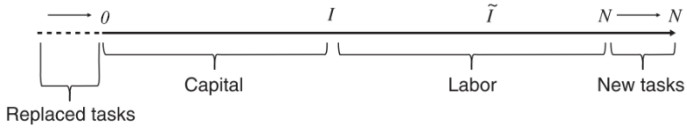


Figure 3: Creation of new tasks in the task spectrum based on Acemoglu and Restrepo (2018c, p. 1497)

[7] This is extensively laid out in Acemoglu and Restrepo (2020b).

as seen in Figure 3. If some tasks become obsolete and are replaced by new ones entirely, the set of tasks shifts or if only new tasks emerge, the set expands. As new tasks z are added as $z \in (N, \infty)$, this implies $z > I$. Thus, labor-intensive tasks are created resulting in increased labor demand and employment in addition to some capital-intensive tasks becoming obsolete. Additionally, according to Acemoglu and Restrepo (2018c, pp. 1490–1491) this increases wages and the labor share.

How these effects play out, is still to be seen, but if AI should be different to previous automation technologies and increase employment, it needs to create more new tasks and complement tasks rather than automating already existing ones. Additionally this analysis does not provide insight into the impacts regarding different skill levels. Acemoglu and Restrepo (2018c, p. 1492) do note, that most of the time, new tasks are available to higher skilled workers while lower skilled workers are at greater risk of substitution, but this has to be questioned with the projected areas exposed to AI, which are displayed in section 4. Acemoglu (2024, p. 23) argues, if high-skilled workers are substituted and replaced instead of lower skilled workers in the same field, there would be ripple effects[8], as higher skilled workers would shift to lower skilled sectors putting additional pressure on wages and employment.

In general, Acemoglu's (2024) task-based framework provides a comprehensive theoretical foundation, regarding the impact of technology and AI on the labor market and for further analysis in this work. Advancements in technology could therefore impact employment in four distinct ways. Automation and deepening of automation reduce employment, whilst complementarity and emerging new tasks increase employment. This thesis operationalizes the task-based framework for the later analysis by translating theoretical mechanisms into task-level measures. Tasks that can be directly performed by AI correspond to automation or *substitution*. Tasks whose productivity is enhanced by AI correspond to *complementarity*. *AI exposure* captures the overall degree to which tasks interact with AI, regardless of direction. Aggregating these task-level measures to jobs reflects the heterogeneous task composition emphasized by the model.

[8] Ripple effects refer to the downward general-equilibrium consequences of task automation. When routine tasks are automated, displaced workers move into lower-skill non-routine manual or service tasks, increasing labor supply and putting downward pressure on wages in those jobs. Acemoglu and Restrepo (2022, p. 1975).

3.3.2 Autor (2025) expertise model

Similar to Acemoglu's task-based framework, D. Autor and Thompson (2025) published a novel model with different assumptions that seems promising to many scholars. This model rather than evaluating tasks of jobs once, focuses on the development of tasks within jobs, deriving changes from an observation they made when comparing O*NET tasks from 1980 to 2018. In their analysis they find obsolete tasks from 1980 being removed from O*NET with new tasks added, changing the composition of tasks in a job. They infer, this could change the expertise required for that job. The following section briefly presents the model and derives its predicted impacts of AI on the labor market.

The model by D. Autor and Thompson is based on three features, that are used to explain changes in employment in the time span from 1980 to 2018. The first feature is *expertise*, which is defined as a "worker's capability to perform specific tasks" (D. Autor & Thompson, 2025, p. 1), where tasks are ranked by their expertise requirements similar to the task-based framework. Additionally, expertise is hierarchical, meaning, more expert workers can perform all tasks with less required expertise but not the other way around (D. Autor & Thompson, 2025, p. 7). The second feature is *bundling*, which implies, that similarly to Acemoglu (2024), jobs are made up of tasks of different expertise levels. Also similar to Acemoglu is an exogenous level of technology that automates certain tasks, with workers needed to perform all non-automated tasks. Therefore, each worker is limited by the most expert, non-automated task in their job. Additionally, all jobs have got some *generic tasks* that any worker can perform (inexpert tasks) but that are unautomatable (D. Autor & Thompson, 2025, p. 7). Examples for these tasks are: boxing lightweight items, greeting customers or counting inventory. (D. Autor & Thompson, 2025, p. 4). The third feature is more like an assumption. It says that technology is advancing, which over time enables more expert tasks to become automated (D. Autor & Thompson, 2025, p. 7). This automation then has three ways to impact labor demand. The first two are similar to Acemoglu: First, automation displaces previously labor-produced tasks and second automation of some tasks improves productivity in remaining tasks of the job (D. Autor & Thompson, 2025, p. 7). The distinct feature is the third impact. When a task becomes automated through technology, the expertise required for that task becomes 0, which lowers the expertise composition of the job. Depending on the job, the automated task could be a

rather expert or a rather inexpert task (D. Autor & Thompson, 2025, p. 7). If the task was the most expert, expertise requirements decrease in this job due to automation, lowering entry barriers and making the job available to more people. In turn raising employment but lowering wages (D. Autor & Thompson, 2025, p. 5). If the task was rather inexpert, the overall expertise level rises, decreasing employment and raising wages, as incumbent workers in the job gain more productivity in remaining tasks. If automation eliminates all expertise requiring tasks in a job, the job becomes entirely inexpert and can be performed by all workers, as only generic tasks remain. When this happens, employment naturally rises in these jobs. The important factor here is, whether a worker of a given expertise gains or loses due to advances in automation depends on the "net effect of the competing forces of capital-labor complementarities and capital-expertise substitution" (D. Autor & Thompson, 2025, p. 8).

Without formally putting up the model, the impacts of technological advancements become apparent using a graphic from their work (Figure 4). On the vertical axis are all tasks $t \in [-\theta,1]$ needed in the economy depending on their required level of expertise. Tasks of $t < 0$, are generic tasks and require no expertise but can also not be automated, therefore, they have to be performed by any human worker. Tasks $0 < t < I_0$ are automated tasks, that require expertise but have been automated using technology. Last, tasks $t > I_0$ are expert tasks, that are not currently automated and thus need human workers. On the horizontal axis are all jobs $\phi \in [0,1]$ in the economy, that are made up of the tasks corresponding to their vertical span of the polygon. For example, the job ϕ' consists of tasks from t'_l to t'_h, thus, a large portion of the job is made up of generic tasks, requiring no expertise, and the more expert tasks are automated. Therefore, no expertise is needed to work in this job. This is different for job ϕ'', which has both, generic tasks, automated tasks and expert tasks, that require human workers with expertise to be performed.

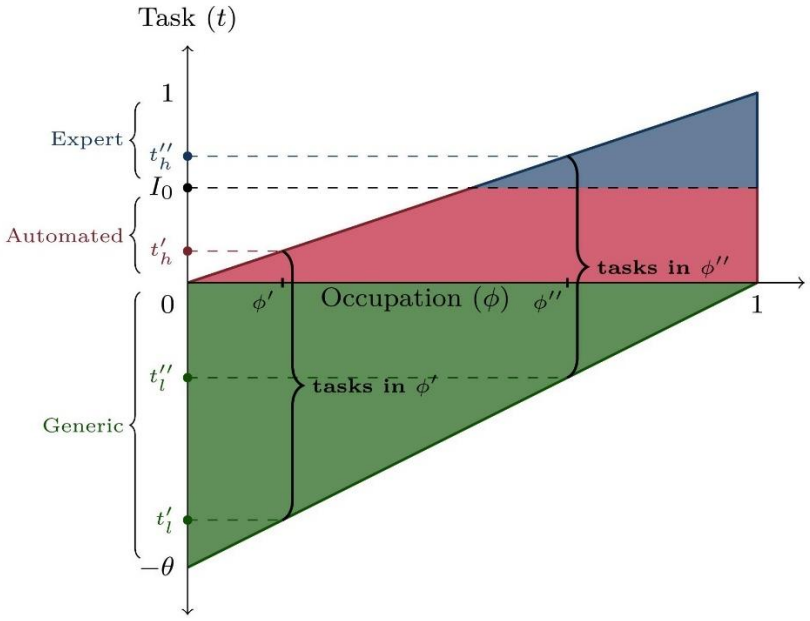


Figure 4: The space of tasks and occupations: expert, automated and generic tasks performed in each occupation ϕ at current state of automation I_0 (D. Autor & Thompson, 2025, 11)

The impact of advancing technology is now visualized as parallel shift upwards of I_0 to I with $I > I_0$. Taking an artificial job ϕ_K with $t_{K,l}$ being the lowest expertise tasks and $t_{K,h}$ being the highest expertise task, there are three outcomes (based on D. Autor & Thompson, 2025, pp. 7–8):

1. If $t_{K,h} < I_0$, there is no effect, as all tasks within the job are already either generic or automated (similar to ϕ')
2. If $I_0 < I < t_{K,h}$, some of the remaining human expert tasks of job ϕ_K become automated, resulting in the share of tasks requiring human expertise shrinking. Therefore, workers in this job can focus more either on generic tasks or on the remaining expert tasks in their job. The required expertise in the job has increased, leading to reduced employment.
3. If $I_0 < t_{K,h} < I$, automation takes over all remaining expertise requiring tasks in the job, leaving the job only with generic and automated tasks. Therefore, this job can now be performed by any worker, rendering the expertise of incumbent workers obsolete. D. Autor and Thompson (2025) say: "a job has become inexpert". As a result, with the job requiring no expertise, employment rises substantially.

By using this model, it also becomes possible that two jobs within the same occupation both become inexpert and require the same amount of expertise (0), in this case the

need to distinguish between the two jobs is omitted. Using the examples of taxi drivers and doctors as jobs, it becomes apparent, how the three effects play out. Let's assume, there is one non-generic task for taxi drivers: knowledge of the streets and maps in the area. As technology advanced, first digital maps and navigational systems became available, eliminating the required expertise of knowing the map by heart, making the job inexpert. Thus, lowering the barrier to entry, lowering wages and increasing employment.

When looking at jobs, that have lower expertise tasks automated, one can think of doctors, that use digital file sorting systems instead of drawers with papers on medical records. The tasks automated through the system include, sorting, classifying and storing records based on some criterion. With doctors not needing to perform these tasks, their jobs do not become inexpert, but rather more productive, as they could use the time spent on organizing files towards working with patients. This could lead to reduced employment, as the same number of doctors can cope with more patients.

To conclude and establish the bridge to AI, D. Autor and Thompson argue, that it depends on which tasks AI will automate and if these tasks resemble the most expert tasks in a job. They argue, if AI leads to a decrease in expertise, by automating the most expert task in a job, its employment will rise, as entry barriers shrink. On the other hand, if AI automates task at the lower end of a job's expertise spectrum, thus increasing overall expertise, employment will fall. The same holds true for new emerging tasks: if new tasks through AI are highly expertise requiring and add to a job's required expertise, employment in that job will fall. If new tasks through AI lower expertise requirements in a job, they expect employment to rise. The analysis of wage impacts is spared in this thesis, but corollarily they find opposing trends: whenever employment increases, wages decrease and vice versa (D. Autor & Thompson, 2025, p. 1).

To test, whether their hypotheses are true, they compare jobs from O*NET in 1977 to 2018 and establish a list of jobs with gains and losses of expertise through automation. Through their analysis they confirm their hypotheses. This analysis cannot be performed as a method of this thesis, as there is no data on evolving task compositions in jobs for the German framework, thus this thesis settles with evaluating the jobs based

on the tasks given at a certain point to obtain exposure, substitution and complementarity values.[9]

3.4 Hypotheses for effects of AI on employment

Using the presented theories from above, no single prediction on AI exposure variables, skill and employment can be made. However, one can derive testable hypotheses regarding AI exposure across skill groups, substitution and complementarity by skill group and the sign of an effect on employment due to these factors. Thus this section provides three hypotheses from the discussed theories to empirically validate in the method section later on.

When discussing a relationship of AI exposure and skill groups, skill-biased technological change comes to mind, where previous waves of automation solely impacted low-skilled manual work. As AI might now be different and complement white collar, high-skilled work, an opposing effect might be seen. It is important to note, that AI exposure has to be understood as "interaction with AI", not automation alone. Additionally, deriving from Acemoglu (2024) the areas, where AI is expected to expand the set of tasks are at the top end of the spectrum, mainly performed by high-skilled workers with a higher share of cognitive tasks. When taking the expertise model into account, it can be argued, that more complex jobs, requiring higher expertise, have more points of contact either through automating some tasks or augmenting others, resulting in higher AI exposure for highly skilled jobs. Thus, the first hypothesis for the empirical analysis later is H1: *Higher-skilled jobs show greater task-level exposure to AI than lower-skilled jobs.*

Turning to substitution and complementarity, historical evidence shows that automation has primarily replaced routine, codifiable tasks, which are more common in lower-skilled jobs. Both the task-based framework and theories of skill-biased technological change suggest that AI continues this pattern by expanding the set of automated tasks at lower skill levels, while simultaneously complementing higher-skilled labor by increasing productivity in remaining tasks. Acemoglu (2024) explicitly argues that new and complementary tasks are more accessible to skilled workers, reinforcing their relative advantage. The expertise model yields a similar prediction, as automation tends

[9] Nevertheless, after presenting an idea of using the using the German GABI classification for this matter to Dr. Ole Teuttloff, he started working on a method to test the expertise model for the German labor market.

to eliminate lower-expertise tasks while increasing the productivity of workers performing higher-expertise tasks. Accordingly, the second hypothesis is: H2: *Lower-skilled jobs face higher substitution risks, while higher-skilled jobs are more strongly complemented by AI.*

Last, the question remains, whether AI already changes employment through complementarity or substitution. As a basis for this analysis, it is assumed, that AI increases productivity and output (SG Analytics, 2025, 3). But as this comes through automation and complementarity, AI exposure alone is insufficient to predict employment outcomes. Rather the means through which it does are interesting to figure out. There are two ways: Based on labor demand theory, employment can rise due to productivity gains and increasing marginal labor productivity or employment can fall due to capital replacing labor in production entirely. The task-based framework is based on automation, where some tasks are replaced and new tasks emerge, therefore it is unclear, whether the substitution of labor by capital will prevail over new tasks and complementarity. Acemoglu (2024) argues, that AI could make certain jobs obsolete and through this reduce employment. Contrary, Autor's expertise framework, argues, automation through AI could make certain jobs inexpert and lower entry barriers, allowing for more employment in these jobs. On the other hand, also based on the expertise model, augmented tasks see decreasing employment due to higher barriers to entry, which is opposing to the idea of coupling increased productivity and increased labor demand. Therefore the expected effects are ambiguous and can be bidirectional. Nevertheless, this work later tries to establish scores of complementarity and substitution to predict changes in labor demand and using these scores, the following hypothesis is put up: H3: *Complementarity with AI is associated with positive employment outcomes, whereas substitution is associated with decreasing employment. The impact of exposure overall can go both ways.*

Next, previously established research will be presented, to understand where to position this research in the current body of literature.

4 AI capabilities, heterogeneous exposure and usage

Section 4 and 5 present currently available empirical evidence. Section 4 first outlines AI's current capabilities based on the definitions of "easy and hard tasks" by Acemoglu (2024), then presents AI usage and exposure based on occupations and at last discusses exposure to AI based on skill and other demographics. This knowledge is needed to understand the then following employment effects of AI exposure, which are discussed in section 5.

4.1 AI capabilities

Understanding whether a job is exposed to AI requires analyzing the underlying mechanisms of the technology. Acemoglu (2024) frames this through a distinction between "easy" and "hard" tasks.

Because AI relies on probabilistic inference rather than deterministic solutions, it excels at "easy tasks" where there is sufficient data and a clear link between actions and observable results (Acemoglu, 2024, p. 17). This reliance on codifiable knowledge combined with probability allows AI to specifically carry out non-routine tasks such as problem-solving, logical reasoning, and perception or recognition. However, because these capabilities are probabilistic, the results can occasionally be inconsistent (Lane & Saint-Martin, 2021, p. 19). Conversely, this reliance on data and metrics renders AI less effective at "hard tasks." These tasks are defined by their dependence on context and the absence of clear outcome metrics (Acemoglu, 2024, p. 18). As a result, humans retain a comparative advantage in creative, social, and uncertain environments, despite experimental progress in AI capability (Max-Planck-Society, 2025).

In general, this analysis is subject to change, as AI capabilities rapidly advance. Using the SWE-benchmark test for programming tasks as an example, OpenAI's LLM ChatGPT was able to increase its score from 4.4% in 2023 to 71.7% in early 2025 (Maslej et al., 2025, p. 130). Some researchers go as far as to say that AI might be able to perform all human tasks within the "foreseeable future" (Korinek & Suh, 2024). Others argue, that AI still mainly is a tool "to answer questions not pose them" (Brynjolfsson & McAfee, 2017) and posit that scientists, innovators and other kinds of people, that figure out, what problem to tackle or what question to raise will be as essential as before (Lane & Saint-Martin, 2021, p. 25; Max-Planck-Society, 2025).

4.2 AI usage and exposure

4.2.1 Occupational exposure

To better evaluate the impacts of AI on occupations and jobs, it is also relevant to get an idea on the occupations and demographics researchers deem most exposed. They define, *AI exposed* occupations, jobs, skills or tasks, as such, that can either be "automated or enhanced through the use of AI" (Chen et al., 2025, p. 7).

In General, Goldman Sachs estimate about 25% of work to be exposed to automation by AI (Hatzius et al., 2023, p. 6), whilst others see approximately 20% of occupations at least 50% exposed to AI (Eloundou et al., 2024, p. 1309). Goldman Sachs find especially high exposure levels for administrative occupations (46% automation) and legal (44%) with physical occupations (6%) and maintenance (4%) being at the other end of the spectrum (Hatzius et al., 2023, p. 6). Georgieff (2024, p. 16) presents a graph of the most exposed occupations based on E. W. Felten et al. (2019) in Figure 5. It becomes apparent that they also evaluate business and legal professions as most exposed with cleaners and agriculture being least exposed. They argue, AI is mainly replacing non-routine cognitive tasks, typically performed in office occupations. Others refer to mostly "white-collar" occupations to being exposed, following the exposure of "blue-collar" occupations in previous automation waves.

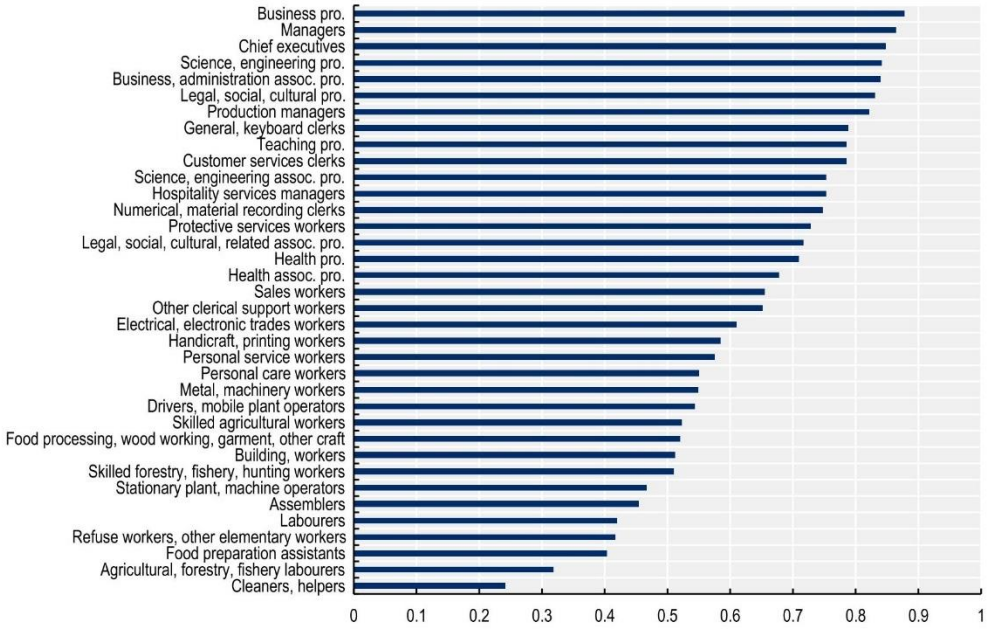


Figure 5: Average exposure to AI across countries, early 2010s (Georgieff, 2024, p. 16)

Generally, for the US-labor market, estimates on the exposure levels on certain professions seem to be matching across studies as Brynjolfsson, Chandar, and Chen (2025, p. 56) find and show in Table 1. They not only evaluate occupations based on exposure but also look for automation (Substitution) and augmentation (complementarity) when evaluating previous studies.

Metric	Least exposed (examples)	Most exposed (examples)
Eloundou et al. (2024) GPT-4 β	• Maintenance and Repair Workers, General • Nursing, Psychiatric, and Home Health Aides • Laborers and Freight, Stock, and Material Movers, Hand • Maids and Housekeeping Cleaners	• Customer Service Representatives • Accountants and Auditors • Software Developers, Applications and Systems Software • Secretaries and Administrative Assistants
Handa et al. (2025) (Overall)	• Taxi Drivers and Chauffers • First-Line Supervisors of Production and Operating Workers • Laborers and Freight, Stock, and Material Movers, Hand • Maids and Housekeeping Cleaners	• Computer Programmers • Financial Managers • Accountants and Auditors • Sales Representatives, Wholesale and Manufacturing
Handa et al. (2025) (Automation)	• Maintenance and Repair Workers, General • Managers, All Other • Nursing, Psychiatric, and Home Health Aides • Driver/Sales Workers and Truck Drivers	• General and Operations Managers • Accountants and Auditors • Software Developers, Applications and Systems Software • Receptionists and Information Clerks
Handa et al. (2025) (Augmentation)	• Cooks • Welding, Soldering, and Brazing Workers • Tellers • Drafters	• Chief Executives • Maintenance and Repair Workers, General • Registered Nurses • Computer and Information Systems Managers

Table 1: Example occupations by exposure category by Brynjolfsson, Chandar, and Chen (2025, p. 56)

Similarly, they also find business administration occupations to be most and manual occupations to be least exposed to AI. Interesting to note is their classification of occupations, that are least exposed to automation but most exposed to augmentation, as they are similar and the ones that AI will not automate but presumably will most enhance and change.

4.2.2 Exposure by demographic

Following is an overview on which demographics are using AI more and are more exposed, concerning wage, skill, education and experience. Regarding wage, Eloundou et al. (2024, p. 1309) find higher exposure for jobs with typically higher wages. They find about 15% Exposure to Gen AI for jobs around 30,000$ and jobs earning more than 100,000$ having almost 50% exposure. Acemoglu (2024, p. 37) finds more evenly distributed exposure regarding hourly wage, as can be seen in Figure 6.

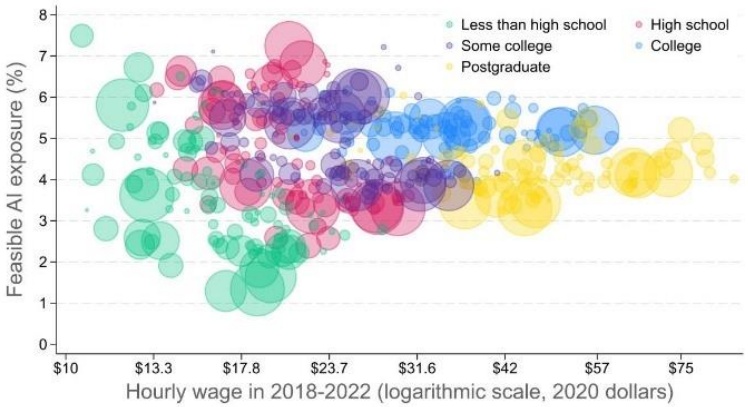


Figure 6: Distribution of AI exposure across the wage distribution (Acemoglu, 2024, 37)

Additionally, Acemoglu (2024, p. 37) finds mostly even distributed exposure across educational background too. Exceptions are: workers with less than high-school education in higher paying positions have low exposure and college graduates have got higher exposure compared to postgraduates in the same wage categories. These findings are contrary to Toney and Flagg (2020), that find 80% of jobs that are "AI-adjacent" require a bachelor's degree. E. Felten et al. (2021), based on their exposed occupation list above, state, that most of the exposed occupations are "white-collar" and require an advanced degree. Some scholars use a separate skill measure instead of education to identify heterogeneous effects. They find effects for all industries and occupations but higher exposure for high skilled workers. They argue, AI can perform tasks of higher skilled individuals with "greater accuracy" (Grennan & Michaely, 2020, p. 30). Lane and Saint-Martin (2021, p. 19) also find higher exposures for higher skilled workers but conclude that, as only some of their tasks are substituted for, they will rather have their jobs changed than disappear. Ernst et al. (2019) predict AI advancements in problem solving and perception lead to complementing low-skilled workers while substituting for high-skilled workers.

Last, some research finds a link between age, experience and exposure. Brynjolfsson, Chandar, and Chen (2025, pp. 4–5) find younger, more inexperienced workers at greater danger of substitution by AI, whilst Humlum and Vestergaard (2025) find

younger, more inexperienced workers use AI more than older ones. Ide (2025) explains the higher exposure for younger workers is routed in the acquisition of tacit knowledge through experience, which AI is unable to have, as it is only trained on explicitly written knowledge. But as there is limited research in this area and effects are heterogeneous, it is to be seen, if other effects emerge, that have not been found yet.

Overall for now, Hartley et al. (2025, p. 11) summarize their findings as follows: Generative AI tools are more commonly used by "younger, highly educated, and higher-income individuals, notably in customer service, marketing, and IT industries", whilst higher exposure levels can be found for more educated, higher paying, "white-collar" office jobs and workers with little experience.

If some of the dynamics discussed will hold true for the German labor market is the first question answered in the method section below and will be the basis, for the analysis concerning AI's impact on employment.

5 Empirical findings on productivity and employment

Before presenting the method of this work and its findings on the relationship between AI and employment on the German labor market, this section elaborates on previous findings on AI and effects on employment in other – especially the US – labor markets. The first part of this section focusses on productivity gains through AI, as these are the foundation for employment change. Then employment effects are presented and additionally, there is a short excerpt on changing of skills.[10] As in general, the findings are heterogenous, where applicable this section displays demographic impacts on these relationships.

5.1 AI's impact on productivity

Following on from the theory section, AI is expected to improve productivity of workers, either by supporting them in completing given tasks faster, more accurately or automating some easy tasks, freeing up time and resources for more valuable tasks. Additionally some tasks, that have already been partially automated can be further enhanced through an increase in innovation (Acemoglu, 2024, p. 4). These gains in productivity are considered to be the main drivers of employment change of previous waves of automation and are expected to lead this one too. Therefore productivity

[10] A section on wage effects can be found in the appendix.

enhancements are important to consider when understanding employment effects. Science agrees that productivity gains can empirically be found. The extent of these effects and their distribution across groups remains up for debate. (Noy & Zhang, 2023).

Reported productivity gains from AI vary widely, ranging from a tripling of output in some settings (Hartley et al., 2025, 11) to more modest increases of 10–45% in meta-analyses and field studies (Jaffe et al., 2024, p. 3; Maslej et al., 2025, p. 268). Survey evidence suggests most workers experience gains below 40% (Necula et al., 2024), while domain-specific studies find substantial effects, such as increases of 44% in material discoveries and 39% in patent filings in scientific research (Toner-Rodgers & Bae, 2025).

But, as AI raises worker productivity, an important question is, who benefits from these gains. Some studies suggest that AI disproportionately helps lower-performing individuals and narrows performance gaps (Choi & Schwarcz, 2023; Dell'Acqua et al., 2023; Noy & Zhang, 2023), while others find that it primarily boosts the output of top performers, potentially widening inequality (Toner-Rodgers & Bae, 2025; Van der Velde, 2020).

Apart from performance biased differences in productivity, there are findings on skill-biased productivity gains as well. Whilst some scholars use their values established for high and low performing workers and argue, higher performing workers are automatically higher skilled, this might not necessarily be the case. As the distinction between high and low-skilled workers is not clearly cut in the literature, these findings have to be taken with caution.[11] Regarding skill-biased research based on education[12], some scholars find more gains for high skilled individuals, in line with the theory of skill-biased technological change, whilst others find the opposite. Chen et al. (2025, p. 22) for example find AI is automating tasks in low-skill jobs while boosting productivity in higher skill jobs. Hartley et al. (2025, p. 8) see low-skilled workers being replaced by highly skilled workers, as these experience more productivity growth compared to low-skilled workers in their analysis. Others find more productivity gains for lower skilled workers, such as Brynjolfsson, Li, and Raymond (2025, 891 and 911) who identify workers in retail and customer support in the lowest quintile boosting their

[11] In the method presented later, there is a more distinct classification and results.
[12] Most studies use workers with bachelor degrees as high-skilled and workers without as low-skilled.

productivity the most (30-36%) to the point where a low-skilled worker with average experience (2 month) using AI is able to perform similarly to a high-skill, experienced (6 month) worker. Some further equalizing effects depending on skill have been put together at Maslej et al. (2025, p. 269) displayed in Table 2.

AI's productivity equalizing effects

Study	Task	Low-skill worker productivity gain	High-skill worker productivity gain
Brynjolfsson et al., 2023	Customer support	34%	Indistinguishable from zero
Dell'Acqua et al., 2023	Consulting	42.96%	16.5%
Cui et al., 2024	Software engineering	21–40%	7–16%
Hoffman et al., 2024	Software engineering	12–27%	5–10%

Table 2: AI's productivity equalizing effects (Maslej et al., 2025, p. 269)

Coming back to Brynjolfsson, Li, and Raymond (2025, 891 and 911), they additionally report an impact of experience on productivity gains through AI. Comparably, a Microsoft study on digital security novices finds novice workers using copilot are 34% more accurate than those without usage, which is a relative gain compared to their expert counterparts. (Edelman et al., 2023, p. 5). Similarly, Del Rio-Chanona et al. (2025), establish a link showing novice workers benefit more from LLMs in easy tasks. On the other hand, Haslberger et al. (2023) report a worsening of equality along the already existing socio-demographic divide. They find older, less educated and female workers have lower usage and benefit less from AI. Despite demographic differences, Toner-Rodgers and Bae (2025) postulate ambiguously: AI tools are powerful, when the user can leverage them effectively, independent of performance, skill and experience.

Productivity gains from AI also affect task completion times and working hours which in turn could affect employment. A Microsoft study finds that Copilot reduces email-writing time by up to 20–25% in some organizations (4% on average), with "power users" saving up to 30 minutes per day (Jaffe et al., 2024, p. 3). These efficiency gains appear to shift time allocation towards more profitable tasks rather than merely reduce workload, as e.g. programmers reallocate time from management to coding and exploratory tasks (Hoffmann et al., 2025, 34), and scientists spend less time on emails and idea generation but more on judgment tasks after adopting AI (Toner-Rodgers & Bae, 2025). Evidence on overall working hours is mixed, with some studies finding reductions and others increases, indicating need for further research (Dominski & Lee, 2025; Jiang et al., 2025, 2).

Overall evaluating the impact of AI on productivity of workers, one can state, that AI has a positive effect on productivity and will change jobs. When asking the question, who benefits from these productivity gains, Georgieff (2024, p. 9) simply concludes: "AI reduces productivity differentials between workers". Hartley et al. (2025, p. 11) on the other hand are more specific and argue: Gen AI is a "substitute for some forms of labor as well as a productivity-enhancing complement for other forms of labor".

Whether these productivity gains have a measurable effect on employment will be the topic of the next section.

5.2 AI's impact on employment

Found employment effects of AI are ambiguous. There are some scholars, that find employment gains in AI exposed jobs (Chandar, 2025), especially when comparing trends before and after the release of ChatGPT in 2022 (Johnston & Makridis, 2025). Similarly, Fossen and Sorgner (2019, p. 24) find lower probabilities of being laid off in AI exposed occupations. On the other hand, there are studies that correlate higher AI exposure to reduced employment and higher unemployment rates (Dominski & Lee, 2025). Similarly, a study using job postings and LinkedIn data found declining demand for AI exposed jobs (Hampole et al., 2025). Most broad studies however find no significant or only limited effects of AI on employment (E. Felten et al., 2021, p. 1; Fossen & Sorgner, 2019; Hartley et al., 2025, p. 10). Additionally, a McKinsey study reported that most CEOs do not see an effect of AI on their workforce within the next three years (Singla et al., 2025, p. 6).

When analyzing the effects of AI on employment on a more nuanced level, scholars do find significant effects depending on whether AI automates (substitutes) or augments (complements) workers in their jobs. Teutloff and Braesemann (2025, p. 716) use postings on online freelance platforms, which usually adapt quickly to changes of condition, to show a significant decline (20-50%) in demand for easily substituted tasks like writing and translation, while demand for skills like machine learning programming has surged. The overall trend can be seen in Figure 7.

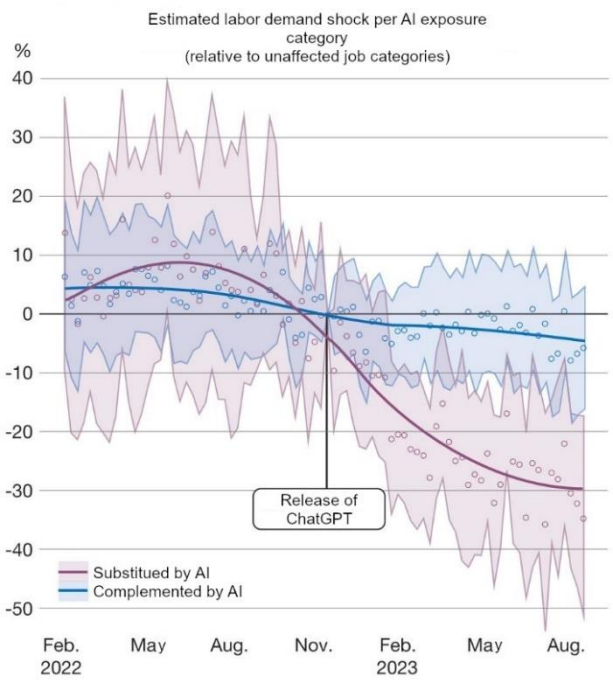


Figure 7: Changes in labor demand around the ChatGPT shock based on Teutloff and Braesemann (2025, p. 717)

Dominski and Lee (2025) demonstrate that jobs reliant on complex reasoning and problem solving have seen declines, as these tasks are substitutable by AI, but manual-task jobs are unaffected and even see slight gains in employment. These findings are consistent with the theoretical expectations and are reported by Brynjolfsson, Chandar, and Chen (2025, p. 3) too. Similarly, other researchers conclude that in jobs, where AI automates tasks, employment decreases, whereas augmentation by AI leads to gains in employment (Johnston & Makridis, 2025), with Chen et al. (2025, p. 18) reporting decreases of 17% for substitution exposed jobs and increases of 22% for complemented jobs.

Considering demographics, studies suggest heterogeneous effects, especially considering skill, education, age and experience. First, as predicted by D. H. Autor et al. in 2003 the observable augmentation in “white-collar” jobs and an immunity to AI for manual labor leads to an effect called “hollowing out of the middle class”, as the middle class is the main socioeconomic group being substituted. Based on this idea, Acemoglu (2021) underscores the current wage and employment polarization for high and low skilled workers he finds in his work. Hartley et al. (2025, p. 8) analyze this effect based on a different cause, they argue low-skilled middle class workers are either

replaced by AI or by high-skilled workers, whose productivities multiply and enable them to perform more tasks in the same time period. Some evidence exists that reinforces this idea, as Chandar (2025) reports higher employment growth for higher educated workers along AI exposed jobs. Thompson (2025) on the other hand observes that the unemployment rate for college graduates has risen above the unemployment for non-graduates, which could be an indicator for a differing trend. Dominski and Lee (2025) argue, workers with higher education do rather face "changes in job structure […] than outright job loss".

Last, age and experience seem to have an impact on how AI exposure affects employment levels. The most comprehensive analysis has recently been published by Brynjolfsson, Chandar, and Chen (2025). Building on their previous analysis in Brynjolfsson (2022), they find no link between AI exposure and employment for older workers but report a significant drop in employment for young workers age 22-25 (Brynjolfsson, Chandar, & Chen, 2025, p. 3). This effect is visualized in Figure 8. This divergence is especially seen in more AI exposed occupations with employment trends for young workers continuing in non-exposed sectors (Brynjolfsson, Chandar, & Chen, 2025, p. 3). This trend could be the beginning of changing employment dynamics that occur not by laying off incumbent employees but rather by hesitating to employ new workers. Additionally they find these effects are persistent across educational groups without college degrees sparing workers from being unemployed (Brynjolfsson, Chandar, & Chen, 2025, p. 4).

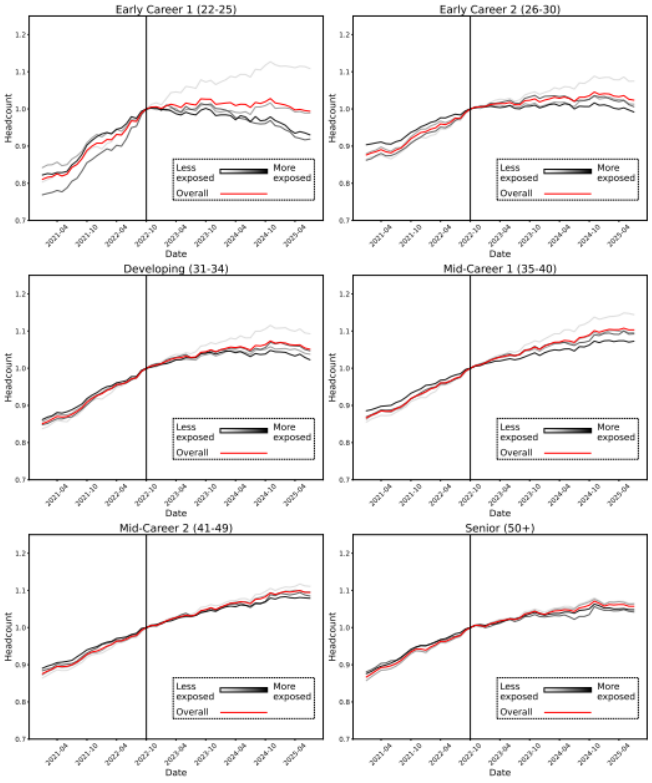


Figure 8: Employment changes by age and automation level (Brynjolfsson, Chandar, & Chen, 2025, p. 36)

The following method and results sections will rely on the findings in this section in order to establish a baseline to compare current employment and AI exposure connections and reaffirm or refute previous findings using a new dataset.

5.2.1 AI's impact on skills

AI adoption reshapes skill demand by automating routine, lower-skill tasks while complementing higher-skill work (Chen et al., 2025, p. 22). As a result, demand rises for AI-complementary skills such as digital literacy and analytical thinking, while demand for easily substitutable skills declines, particularly in routine customer-facing roles (Mäkelä & Stephany, 2024b, p. 36). Empirical evidence shows that automation-prone jobs experience a substantial reduction in required skills, whereas augmentation-prone jobs see skill expansion. These shifts are already reflected in worker reallocation across fields and changing educational choices (Horowitch, 2025). Beyond technical skills, AI also affects language and collaboration: language barriers are significantly reduced, while reliance on AI tools lowers human-to-human collaboration (Hoffmann et al., 2025, p. 30; Jaffe et al., 2024, p. 8).

5.2.2 Findings for specific industries

Early and robust AI impacts are especially visible in three specific industries: software development, finance, and customer service, where adoption rates and productivity gains are particularly high. From these industries possible effects for the rest of the economy can be inferred. In software development, rapid improvements in large language models have led to significant productivity increases, especially for routine coding tasks, while more complex problem-solving remains human-led (Cui et al., 2024, p. 12; Edelman et al., 2023, p. 3; Hoffmann et al., 2025, p. 48; Peng et al., 2023, p. 5). In finance, AI builds on earlier digitalization, improving data processing, forecasting, and decision support, fully replacing professionals that do not adapt towards non-data-driven stocks (Grennan & Michaely, 2020). Customer service shows the strongest substitution effects, as chatbots and automated systems increasingly replace standardized interactions, reducing labor demand for routine roles (Brynjolfsson, Chandar, & Chen, 2025; Brynjolfsson, Li, & Raymond, 2025). Across these sectors, AI primarily

substitutes repetitive tasks while complementing analytical, supervisory, and creative functions, reinforcing existing skill hierarchies rather than eliminating skilled work.

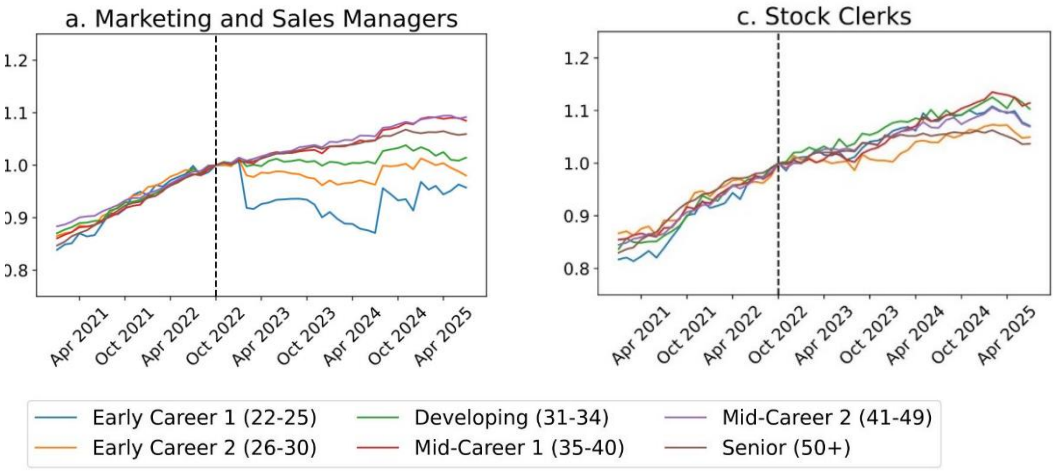


Figure 9: Headcount of marketing / sales managers and stock clerks by age based on Brynjolfsson, Chandar, and Chen (2025, p. 11)

When comparing the employment trends of marketing and sales managers to stock clerks the other divide becomes apparent (Figure 9). Whilst employment for young people (blue line) drops significantly for the cognitive job of marketing and sales managers, the trend remains constant for manual labor stock clerks.

5.3 The research gap and novelty of this work

Existing empirical research on Artificial Intelligence and labor markets has so far relied almost exclusively on U.S.-based data sources such as O*NET, the SOC classification, and task descriptions tailored to the American labor market. While these studies have produced valuable insights, their applicability to other institutional contexts – particularly continental European labor markets with different occupational structures and training systems – remains limited. To date, no study has systematically evaluated AI exposure, substitution, and complementarity for the German Classification of Occupations 2010 (KldB 2010, revised 2020) at the level of its detailed task descriptions.

This thesis closes this substantial research gap in three distinct ways. First, it provides the first complete indexation and structuring of all tasks contained in the KldB 2010 (2020 version). Although the *German Federal Employment Agency*[13] publishes job-based descriptions, these exist only in unstructured PDF format and are therefore not directly usable for empirical analysis. By extracting, cleaning, and systematizing all

[13] Original: Bundesagentur für Arbeit.

8,864 individual tasks across 1,297 jobs, this thesis generates a novel dataset that did not previously exist in any academic or administrative form.

Second, this work introduces a task-based AI evaluation for the German labor market that mirrors but substantially extends previous approaches based on O*NET. Using validated prompt-engineering methods inspired by Eloundou et al. (2024) and Chen et al. (2025), each KldB 2010 task is scored along three dimensions—AI exposure, substitution potential, and complementarity potential. This constitutes the first attempt to translate state-of-the-art LLM-based task scoring to a non-English, non-U.S. occupational classification. The resulting dataset enables cross-occupational and within-occupational comparisons and robustness checks that were previously impossible for Germany.

Third, the thesis links these newly constructed AI measures to actual employment developments in Germany after the ChatGPT shock of 2022. While several studies have compared pre- and post-AI patterns in U.S. employment, no equivalent analysis has been carried out using German employment data at the five-digit[14] occupational (job-)level. By combining quarterly employment data (2012–2025) with the constructed task-level AI measures, this thesis offers the first empirical evaluation of how AI exposure, substitution, and complementarity relate to early employment dynamics in Germany's skill-segmented labor market.

Overall, the novelty of this work lies in establishing a new empirical foundation for studying AI and labor in Germany. It contributes a fully structured task dataset, introduces validated LLM-based scoring for German tasks and jobs, and provides first-evidence estimates of how AI-related task structures correlate with emerging employment trends. This combination positions the thesis as a meaningful extension to the international literature and a unique contribution to German labor market research.

[14] The explanation regarding digits is found at the beginning of section 6.1.

6 Method

The goal of this section is to find impacts of AI exposure, substitutability by AI and complementarity to AI on employment on the German labor market at the job level. To achieve this, a dataset of 778,200 entries is constructed, that will be evaluated.

The method section overall is split into three parts, that each contribute individually and combined to the current body of literature: The first part explains, how to obtain occupations, jobs and all tasks from the publications on jobs and tasks by the German ministry of labor. In the second part a novel but already validated method is used to label all tasks published with regards to the explanatory variables (AI exposure, substitution score and complementarity score) and the third section establishes a relationship between the explanatory variables and the dependent variable of employment using inferential statistics.

6.1 Obtaining the dataset consisting of: occupations, jobs, tasks, AI exposure, substitution score and complementarity score

To achieve the desired goal of finding an impact of AI exposure, substitutability and complementarity on employment levels, some steps need to be undertaken that no other research has done before. The analysis uses the KldB 2010 with its 1300 jobs of which 1297 are examined, excluding the three military jobs[15]. Overall, the KldB 2010 clusters these jobs in 9 areas:

1. Agriculture, forestry, animal husbandry, and horticulture
2. Raw material extraction, production, and manufacturing
3. Construction, architecture, surveying, and building services engineering
4. Natural sciences, geography, and computer science
5. Transportation, logistics, protection, and security
6. Commercial services, goods trading, distribution, hotel, and tourism
7. Business organization, accounting, law, and administration
8. Health, social services, teaching, and education
9. Languages, literature, humanities, social sciences, economics, media, art, culture, and design

[15] Employment levels in military occupations are not subject to the market in the same way as other occupations and are therefore excluded.

Each of these areas then further fans out into sub-areas and further into 700 specific occupations resulting in a four-digit ID for each occupation. Afterwards a fifth digit is added to mark if the occupation is performed at helper (1), skilled worker (2), specialist (3) and expert (4) level resulting in a five-digit code marking the job. This digit is used to represent high- and low-skilled workers according to the German classification of occupations. Thus, high-skilled workers are workers in jobs on level three – "Specialist" and level four – "expert", while low-skilled workers are workers in jobs at level one – "helper" and level two – "skilled worker". How this classification is constructed in detail is explained by the German Ministry of Labor (2011) on their website. Not all occupations have got all four skill levels, as doctors and lawyers for example are always experts, whilst e.g. "cleaners in the construction industry" have no occupations at the expert level. So, e.g in the case of doctors occupation and job are identical. These four-digit occupational and five-digit job IDs build the measuring units for the following analysis.

Each 5-digit job has a designated list of three to 15 tasks that are unique for the specific job ID, which are made public by the *German ministry of Labor*[16]. These tasks are used to construct the explanatory variables (AI exposure, substitutability score and complementarity score). [17] To help with understanding, the example ID 12102 is presented here and used throughout:

1. The first four digits 1210 correspond to the occupation: "Gardening profession (without specialization)".
2. Adding the fifth digit, the occupation becomes the job: "12102 - Gardening professions (without specialization) – skilled worker"[18].
3. This job has six tasks under its name, including:
    a. "Create production areas, propagate trees, vegetables, fruit trees, shrubs, or ornamental plants, grow, harvest, store, market, and ship" and
    b. "Take on administrative tasks and business management activities in the horticultural business, e.g. prepare cost calculations, observe markets, record cost-benefit ratios".

[16] Original: Bundesagentur für Arbeit (2020).
[17] For a full example in German refer to the appendix.
[18] There also are 12101 – helper, 12103 – specialist and 12104 - expert with each having different tasks. For more, refer to the appendix.

As all tasks and jobs are made public as a pdf, they are not yet in usable data format. Therefore, all 8864 tasks of all KldB 2010 jobs first need to be indexed using a Python script and are then manually sorted.[19]

After obtaining all tasks, each task is rated considering two scores. First, the level of AI exposure is determined on a scale of 0 to 1. For this analysis, a task is considered *exposed to AI*, if using AI yields "a reduction in time it takes to complete the task by at least 50%" (Eloundou et al., 2024, p. 16). This score is higher if the task is directly exposed and lower, if additional applications using AI are needed to achieve a 50% reduction. The second score is constructed regarding substitution and complementarity of the task. *Substitution* is defined as "displacement [of the task] as generative AI substitutes human labor" (Chen et al., 2025, p. 6), whilst AI can "*complement* human labor by improving task efficiency" indicating *complementarity* (ibid.). There are two more options for this score: either tasks are not exposed at all or they are directly linked to AI development. To rate all 8864 tasks, OpenAI's gpt-oss-120b[20] model and two prompts, that can be found in appendix D, are used. Through these prompts, each task is assigned with an AI exposure value and a value regarding substitution and complementarity score.

Scoring of the individual tasks works similar to a process first efficiently used by Eloundou et al. (2024). This process uses a complex prompt developed through the process of prompt engineering[21] that is given to an AI, instructing it to evaluate the task presented based on the prompt. During the last year, this method has become widely adapted and validated for analyzing and evaluating written instructions, as other examples show (Aeppli & Wilmers, 2022; Benítez & Parrado, 2024; Brynjolfsson, Chandar, & Chen, 2025; Chen et al., 2025; Dominski & Lee, 2025; Hampole et al., 2025; Jiang et al., 2025; Maslej et al., 2025; Meisenbacher et al., 2025; Resh et al., 2025; Schmidt et al., 2025; Teutloff et al., 2025; Tomlinson et al., 2025). Most studies find high correlations (>90%) between AI's ranking of tasks and human experts, validating the use. As most of the studies have used the O*NET dataset with its jobs and descriptions, the attempt to label the German job classification is a novelty. The

[19] The script and newly constructed data set is available at request at moritz.meyer@mail.de.
[20] This specific model is used, because its capabilities are analogous to ChatGPT4o mini, which was used to evaluate the prompts used in their original version and because this specific model is made available through an API by the University of Münster for students to use.
[21] To learn more about prompt engineering, refer to Resh et al. (2025, p. 17).

prompts used in this work were developed by Chen et al. (2025). They created two prompts for two values: First is the AI exposure value, which is directly related to Eloundou et al. (2024) and uses very similar wording. The categories are:

1. "E0": No exposure;
2. "E1": Direct exposure;
3. "E2": Exposure by LLM-powered applications;
4. "E3": Exposure given image capabilities.[22]

Second is a skill exposure: Chen et al. (2025) evaluate through a prompt, whether a skill in O*NET can be classified as:

1. "S1": Connected to the development of AI
2. "S2": Complemented by AI
3. "S3": Substitutable by AI
4. "S4": Irrelevant to AI.

The task then for the AI is, to assign two values to all tasks using this classification and give reasoning. Coming back to the example of job "12102 - Gardening professions (without specialization) – skilled worker", the tasks are rated as follows:

1. The task "Create production areas, propagate trees, vegetables, fruit trees, shrubs, or ornamental plants, grow, harvest, store, market, and ship" is rated as **E0 – No exposure;**, with the reasoning, that the tasks requires manual labor and precise physical measurements and *S2* with the reasoning: "AI can help providing predictive models for crop yields, optimizing planting layouts, generating marketing copy, automating inventory tracking, and offering planning insights but the task itself remains manual labor".
2. The task "Take on administrative tasks and business management activities in the horticultural business, e.g. prepare cost calculations, observe markets, record cost-benefit ratios" is rated as *E2* with reason being "administrative and business-economic duties that plain LLMs can only partially support, but LLM-powered tools could automate data collection, calculations, and reporting enough to cut an experienced manager's workload by at least half" and *S2* with the reason "AI can automate data aggregation, produce preliminary financial reports, and provide

[22] To learn about how these categories are defined in the prompt, please refer to the appendix.

market insights, core tasks like cost accounting, market monitoring, and cost-benefit analysis still rely on human interpretation and strategic judgment, so the skill is 'Complemented by Gen AI.' "

Both prompts are used by Chen et al. (2025) under a similar model as in this work and both prompts are validated by an agreement rate of AI output and expert rating by at least 80,8% (Eloundou et al., 2024, p. 1314). Nevertheless, a manual rating and comparison of 50 tasks has been performed, to ensure additional validity. [23] This manual rating resulted in agreement of 76 % for the AI exposure value and for 80% in the skill value. As this thesis is only written by one author, there is no second person, rating the same tasks for a comparison but through AI rating the tasks, personal objectivity is ensured.[24]

As AI does not always provide scores the same way, a script gets rid of the reasoning text afterwards and homogenizes the outputs to obtain standardized results.[25] These results are transformed as follows to achieve linear scores: E1=1, E0=0, E2=0.66 and E3=0.33. Afterwards the AI exposure score for the job is calculated as the mean of all task scores of that job. Calculating the substitution score and complementarity score works a little differently, as the share of tasks labelled S3 is taken as the substitution score and the share of tasks labelled S2 is taken as the complementarity score.[26] Using the example 12102 from above, the AI exposure score is (0+0.66)/2= 0.33, as one task was rated E0 and one task was rated E2. The substitution score is 0, as no task was labelled S3, but the complementarity score is 0.5, as half the task were rated S2.

When comparing this version of obtaining these values, to some of the versions used on the American O*NET database, it becomes apparent, that this analysis does not use any work share data, to weigh the tasks. Although, this data partially exists for Germany in the SIAB[27] data set by the institute for employment research, it is not available to students and can therefore not be used here.

[23] All Ratings can be found in the appendix0.
[24] LLM-Models might still be subject to bias by their creators (e.g. OpenAI).
[25] Example: Sometimes the Output was: e.g. "**E0 – No exposure;**"; "**Score: E0 – No exposure**"; "E0; ". All were transformed to be "E0".
[26] For a full example refer to the appendix.
[27] Original (in German): Stichprobe der Integrierten Arbeitsmarktbiografien.

6.2 Analyses regarding occupation, job and scores

Results will be presented as follows: First, the descriptive results of these previous computations are presented as shares for each of the variables AI exposure, substitution score and complementarity score. Then basic means and standard deviations for each variable in general and means and standards deviations for each variable depending on the 5th digit of the job ID, which resembles the skill level are reported. Afterwards an ANOVA tests for significant differences between the different skill levels overall. But as the data used is nested within occupational skill level (job), a simple ANOVA might misinterpret or entirely miss the true relationship of occupation, skill and variables. Therefore, more elaborate analyses are needed. Suitable in this case, are so called random intercept (RI) and random intercept fixed slope (RIFS) models, that are used for nested data with up to 2 predictors.[28] As the Akaike Information Criterion (AIC) score is lower for the random intercept fixed slope model (-393 and -605), only this model is used in the analysis. The AIC is a widely used measure for model selection that balances model fit and complexity. It is defined as

$$\text{AIC} = 2k - 2\ln(\hat{L}),$$

where k is the number of estimated parameters and $\hat{L}$ is the maximized value of the model's likelihood function. The AIC penalizes models with more parameters to discourage overfitting, while rewarding those that achieve a high likelihood. When comparing competing models estimated on the same dataset, the model with the lowest AIC is preferred because it is expected to minimize information loss relative to the true data-generating process. Importantly, AIC does not test hypotheses; rather, it provides a relative measure of model quality within a given set of candidate models.

The random intercept fixed slope (RIFS) model works as follows: A random intercept is estimated for each occupational group (4-digits). This allows the baseline level of the dependent variables – such as AI exposure, substitution score, or complementarity score – to differ systematically across the 4-digit occupations. Conceptually, each 4-digit occupation receives its own vertical shift of the regression line, reflecting occupation-specific average levels of the outcome.

At the same time, the predictor variable derived from the fifth digit of the job code ("skill level") enters the model as a fixed slope. This implies that the effect of this

[28] Using a random intercept, random slope model is not possible with the data at hand.

predictor is assumed to be constant across all occupations: while occupations differ in their baseline starting point (intercept), their subclass jobs are assumed to respond in the same way to variation in the level variable. The model therefore has the form:

$$y_{ij} = \beta_0 + u_j + \beta_1 \text{skilllevel}_{\text{ij}} + \varepsilon_{ij},$$

where u_j captures the 4-digit occupation-specific deviations from the overall intercept, and β_1 represents the uniform effect of the skill level variable across all groups.

This modelling structure serves two purposes in the context of the thesis:

1. Capturing between-occupation differences:

   The random intercept quantifies how much AI exposure (or related outcomes) varies systematically *across* occupations.

2. Capturing within-occupation variation:

   The fixed slope for the level predictor captures systematic differences *within* occupation groups (5th digit) comparing jobs concerning skill level. Because the slope is fixed, these within-group effects are interpreted as homogeneous across all occupations.

These calculations are performed for all three variables.

6.3 Analyses regarding scores and employment

As for the previous section, AI exposure, substitution score and complementarity score were dependent on occupation and skill level, for the second part of the analysis, they will become the independent/explanatory variable used to explain differences in employment after the ChatGPT shock of November 2022, which made Gen AI available to the world. The used employment data is published quarterly by the Ministry of Labor on a 4-digit basis that can be manually amended to get 5-digit level employment data using a pivot table. Precisely, this work uses the definition in Section 7 (1) of Book IV of the German Social Code (SGB IV)[29] "*Employment* is work performed for someone else, particularly in an employment relationship." The statistic on employment used will include all employees subject to social security contributions recorded by the German Ministry of labor.

[29] Original: § 7 Abs.1 Viertes Buch Sozialgesetzbuch (SGB IV).

The following analysis uses quarterly data on the 5-digit level spanning from December 2012 to March 2025 indexed to 100 in Q3 2022, as this was the quarter of the launch of ChatGPT. A method, that most other scholars use too (Chen et al., 2025, p. 14). Before performing any analysis regarding employment, all jobs, that have <500 incumbent workers, are excluded, truncating the dataset in the same way, the German ministry of labor does, when it performs analyses with its data. The analysis will first provide graphs for the relationship of AI exposure, substitution score and complementarity score for the timespan 2020-2025 separately, before then performing a multiple regression and a moderated regression in which employment changes are numerically explained by the three occupation-specific AI measures combined with the job-based skill level. As the AIC of the multiple regression is lower (6648 compared to 6652) and therefore better, this model is used to evaluate the findings.

Because employment fluctuates on a quarterly bases, this model uses a window-based strategy of computing means whilst preserving comparability across time. This window-based strategy works the following: For each job i, employment is observed quarterly from 2021 to 2025. Two anchor quarters—2022Q3 and 2025Q1—serve as reference points representing a pre-AI-adjustment and a post-AI-adjustment period. For each anchor quarter, the analysis considers the four quarters leading up to it (a one-year window). The mean employment level within each window is calculated, and the difference between the two means represents the change in average employment:

$$\Delta\text{employment}_i = \bar{E}_{i,2025} - \bar{E}_{i,2022}.$$

This windowed difference approach smooths short-term fluctuations and yields a robust measure of job-based employment change.

The resulting employment change is regressed on the three AI-related predictors: AI exposure (AI_exp), substitution score (subst), complementarity score (compl) and the job's skill level, derived from the ID's 5th digit. The aimed for empirical model is specified as a linear mixed-effects model with random intercepts at the 4-digit occupation level:

$$\Delta\text{employment}_{ij} = \beta_0 + u_j + \beta_1 \text{AI_Exp}_{ij} + \beta_2 \text{Subst}_{ij} + \beta_3 \text{Compl}_{ij} + \beta_4 \text{skilllevel}_{ij} + \varepsilon_{ij},$$

where j indexes the 4-digit occupation and $u_j \sim \mathcal{N}(0, \sigma_u^2)$ captures unobserved heterogeneity between occupations. The random-intercept structure allows each occupation

to have its own baseline level of employment change, while assuming that the effects of AI exposure, substitution, complementarity, and skill level are homogeneous across groups.

During estimation, the optimizer returned a singularity warning. A model is singular when at least one random-effect variance is estimated to be numerically zero. In this case, the variance of the occupation-level intercept collapses to:

$$\hat{\sigma}_u^2 \approx 0.$$

A singular fit does not invalidate regression, but it signals that the skill-level specification does not add information over an ordinary least squares (OLS) model. In this case, the random-effect component collapses, and the model reduces to this OLS:

$$\Delta\text{employment}_i = \beta_1 \text{AI_Exp}_i + \beta_2 \text{Subst}_i + \beta_3 \text{Compl}_i + \varepsilon_i.$$

An Ordinary Least Squares (OLS) model is the standard estimation method for linear regression models. It identifies the linear combination of predictors that best explains the variation in the dependent variable. “Best” is defined as the parameter values that minimize the sum of squared residuals, i.e. the squared differences between the observed values of $\Delta employment_i$ and the values predicted by the model.

Formally, OLS chooses the coefficient vector $\hat{\beta}$ that solves:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{N} (\Delta employment_i - X_i\beta)^2.$$

This produces the line (or hyperplane) that fits the data most closely in a least-squares sense. The OLS regression model quantifies employment differences using three coefficient vectors: β_1 for AI_exp, β_2 for subst and β_3 for compl. When presenting the results, higher coefficients will imply higher impacts of the corresponding variable. An analysis on wages will not be performed, as the stickiness of wages will presumably hinder observable changes for now and as the data by the German ministry of labor is only available yearly (Davis & Krolikowski, 2025).

The next section will now show the results of all analyses and calculations performed.

7 Results

7.1 Descriptive

As the method section was split into three parts, this section is also split into three parts. First are the results of evaluating the tasks and clustering them to job-level scores, including some first robustness checks, to prove the accuracy of the used prompts and method. Second are the results of the analyses of combining jobs and scores. The third part then connects these scores to the dependent variable of employment.

First, scoring all tasks, provides the following shares presented in Tables 3 and 4. The values are presented and compared against the values by Chen et al., who used the same prompts on O*NET.

AI Exposure Score	Share of tasks	Chen et al. (2025)
E0 – No exposure	72,26%	55,08%
E1 – Direct exposure	14,43%	28,33%
E2 – Exposure through LLM powers Apps	13,04%	16,15%
E3 – Exposure given image capabilities	00,24%	00,44%

Table 3: Shares of tasks rated based on AI exposure

Gen AI skill score	Share of tasks	Chen et al. (2025)
S0 – Irrelevant to Gen AI	22,03%	48,91%
S1 – Direct Gen AI relevant skill	00,39%	12,19%
S2 – Complemented by Gen AI	76,21%	36,45%
S3 – Substituted by Gen AI	01,34%	02,45%

Table 4: Shares of tasks rated based on the skill exposure measure by Chen et al. (2025)

The tables show the distribution of tasks for both AI classifications. The AI exposure score shows a similar pattern, to what Chen et al. (2025) find for the O*NET data, albeit with different exact numbers, providing a first robustness check on the validity of the scores. It becomes apparent, that for the German KldB 2010 almost three quarters of tasks are not exposed to AI in general, in the sense, that it reduces time to fulfill this task by more than 50%. When using the more broadly written prompt for Gen AI skills, only about one quarter of tasks are irrelevant but there are three quarters of tasks, in which Gen AI can be complementary. When comparing the values for the Gen AI score with the ones found by Chen et al. (2025), there is quite a dramatic difference, although some of the structure remains. How these differences might be explained will be estimated in the discussion section.

To give further validation to the method, the following Tables 5 and 6 show the 16 least exposed and ten most exposed jobs regarding the calculated AI exposure score. They are presented next to the score computed by E. W. Felten et al. (2019), that evaluated AI exposure through hard measures rather than prompts. Their score has a mean of 0.67, SD of 0.04 and spans from 0.56 to 0.73. This comparison has to be taken cautiously, as their jobs from O*NET cannot directly be transformed to KldB 2010 jobs. Nevertheless, this thesis tries to be as accurate as possible and uses the official transfer key provided by the German Ministry of Labor (2021) connecting KldB 2010 to ISCO-08, then transferring from ISCO-08 to SOC to obtain the O*NET name as described in Hoen (2016).

There are 309 (23,8%) jobs with an AI Exposure score of 0. Of these 309 jobs, 16 jobs also have a substitution and complementarity score of 0. These are the least exposed jobs in the KldB 2010 classification. There is no hierarchy amongst them, as all have score 0 in all three counts.

ID	Job name	E. W. Felten et al.
11211	Helpers in livestock farming	N/A[30]
11322	Occupations in horsekeeping: riding – skilled tasks	0.634
11342	Coachman – skilled worker	N/A
11711	Occupations in forestry – helper	0.637
21311	Occupations in glass-making-helper	0.626
22201	Occupations in color coating and varnishing (without specialization) – helper	N/A
24301	Occupations in treatment of metal surfaces (without specialization) – helper	N/A
26262	Occupations in installing and servicing electrical cables – skilled worker	0.670
33122	Composition floor and terrazzo-layers – skilled worker	0.624
33352	Roller shutter and jalousie installers – skilled worker	0.606
63301	Gastronomy occupations (without specialization) – helper	0.637
82101	Occupations in geriatric care (without specialization) – helper	0.645
82401	Occupations in funeral services – helper	0.644
93332	Occupations in turnery and toy manufacture – skilled worker	0.641
93352	Chandlers – skilled worker	0.641
94283	Occupations in acting, dancing, athletics and related occupations (with specialization, not elsewhere classified) – specialist	N/A

Table 5: 16 jobs least exposed to AI

[30] Felten et al. do not provide a score for these jobs.

All jobs classified fall below the established mean by Felten, giving a second robustness check on the validity of the AI exposure score.

The next Table 6 shows the ten most exposed jobs regarding AI exposure, again compared to the scores by E. W. Felten et al. (2018). The table will also list their substitution (Subst.) and complementarity (Compl.) scores. All scores are rounded to three digits.

ID	Job name	AI_exp	Subst.	Compl.	E. W. Felten et al.
61122	Occupations in sales – skilled worker	0.932	0.2	0.8	0.724
82223	Occupations in wellness – specialist	0.915	0	1	0.668
91184	Occupations in philology – expert	0.887	0	0.833	0.694
41103	Occupations in mathematics – specialist	0.864	0	1	0.731
73204	Occupations in public administration – expert	0.864	0	1	0.669
73323	Library occupations – specialist	0.864	0	1	0.680
91124	Occupations in English and American philology – expert	0.864	0	1	0.694
91354	Occupations in demography – expert	0.864	0	1	0.731
43423	Occupations in programming – specialist	0.857	0	0.857	0.727
84184	Teachers in schools of general education – expert	0.833	0	0.833	0.707

Table 6: 10 jobs most exposed to AI

For the ten most exposed task, the table also provides 8 out of 10 scores well above average exposure for Felten et al. (2018). Some scores do not always truly resemble the same jobs in the American O*NET as the German KldB 2010, resulting in differences.[31] Therefore this can only be seen as partial robustness check.

Next, using the very detailed classification of the German KldB 2010, the mean scores for each of the four different skill levels existing in most occupations are evaluated and presented in Table 7. These are: helper (1), skilled worker (2), specialist (3) and expert (4). Values are rounded to the third decimal.

[31] Example: 91354 “Occupations in demography” becomes 2120 “mathematician” in ISCO – 08 and afterwards becomes 15 – 2011 “Actuaries” in O*NET.

Skill Level	Mean AI_exp	SD	Mean Subst_score	SD	Mean Compl_score	SD	n
Overall	0.232	0.206	0.019	0.076	0.760	0.260	1297
Helper	0.058	0.114	0.062	0.135	0.304	0.226	60
Skilled worker	0.143	0.185	0.037	0.104	0.611	0.258	366
Specialist	0.249	0.184	0.009	0.053	0.858	0.181	301
Expert	0.342	0.200	0.002	0.017	0.889	0.154	270

Table 7: Means of AI exposure, substitution score and complementarity score based on skill level

It becomes apparent that higher-skilled jobs seem to have higher exposure scores, lower substitution scores and higher complementarity scores. Whether these differences are significant is tested using inferential analyses in the next section. Further, there will be tests on different scores between occupations and within occupations.

7.2 Inferential statistics

In this section, inferential statistics answer the following questions: 1. Are different occupations and skill levels differently exposed, substituted or complemented by AI? 2. What variables already have an observable impact on employment?

7.2.1 Impact of skill on AI exposure, substitution score and complementarity score

Although the means from above do already hint at a connection between skill levels and exposures, an ANOVA tests if results are significant. The ANOVA's results can be found in Table 8 below.

Variable	ANOVA	ANOVA_p	Correlation_r	Correlation_p	Kruskal-Wallis χ^2	Kruskal-Wallis p
AI_exp	94.592	0.000[32]***	0.4238	0.000 ***	286.109	0.000 ***
Subst.	25.470	0.000 ***	-0.2248	0.000 ***	85.415	0.000 ***
Compl.	262.559	0.000 ***	0.5645	0.000 ***	429.806	0.000 ***
Significance: *** p<0.001 ** p<0.01 * p<0.05 ns=not significant						

Table 8: ANOVA results for skill variable correlation

It can be seen, that AI exposure differs substantially across occupational skill levels. The ANOVA yields a highly significant result ($F = 94.592$, $p < 0.001$), indicating strong variation in mean exposure between groups. The Pearson correlation between skill level and AI exposure is moderate and positive ($r = 0.4238$, $p < 0.001$), suggesting a clear upward trend: higher-skilled jobs are noticeably higher exposed to AI

[32] Exact value: $4.75*10^{-133}$ treated as zero.

technologies. A Kruskal–Wallis test confirms these differences non-parametrically ($\chi^2 = 286.109$, $p < 0.001$).

Regarding substitution, there are significant results across skill groups. The ANOVA shows clear differences ($F = 25.470$, $p < 0.001$), and the Pearson correlation reveals a weak but significant negative association between skill level and substitution score ($r = –0.2248$, $p < 0.001$). This indicates that lower-skilled jobs have higher substitution risk. The Kruskal–Wallis test again confirms significant group differences ($\chi^2 = 85.415$, $p < 0.001$).

Complementarity exhibits the strongest variation among the three outcomes. The ANOVA shows a very large F-statistic ($F = 262.559$, $p < 0.001$), and the Pearson correlation demonstrates a substantial positive association between skill level and complementarity ($r = 0.5645$, $p < 0.001$). Specialists and experts consistently are much higher complemented compared to helpers and skilled workers. This pattern is corroborated by the Kruskal–Wallis test ($\chi^2 = 429.806$, $p < 0.001$).

These metrics find base line results for an impact of skill level on all three variables. But as mentioned in the method section the data used in this case is nested with occupation (first 4-digits) and then for skill level (5th digit). Thus, a more elaborate analysis called random intercept fixed slope model (RIFS) is needed, which is used for nested data with up to 2 predictors. This model yields significant results between occupations (4-digit) for substitution score and complementarity score and significant results within occupations for all three variables: AI exposure, substitution score and complementarity score.

The RIFS model provides the following results for the relationship of *AI exposure*, occupations and skill: The intercept is not statistically different from zero, meaning that there exists no difference for the 4-digit occupations regarding AI exposure. But occupational skill level (5th digit) is strongly positively associated with AI exposure. The estimated coefficient on skill level is 0.091 (SE = 0.0057; t = 15.8; $p < 0.001$). Therefore, moving from the lowest to the highest skill level within the same 4-digit occupation (from level 1 to 4) is associated with an increase in AI exposure of about 0.27 points (3 × 0.091). Predicted values (ignoring occupation-specific random intercepts) rise from roughly 0.066 at level 1 to 0.362 at level 4, indicating a sizeable

within-occupation gradient. This effect can be graphically visualized using the output of the RIFS model in Figure 10. Each gray line in the figure depicts one occupation on the four-digit level with the intercept being the base exposure and the slope being the change in exposure per skill level change. Therefore, this analysis shows a significant difference in AI exposure within occupations but not across occupations.

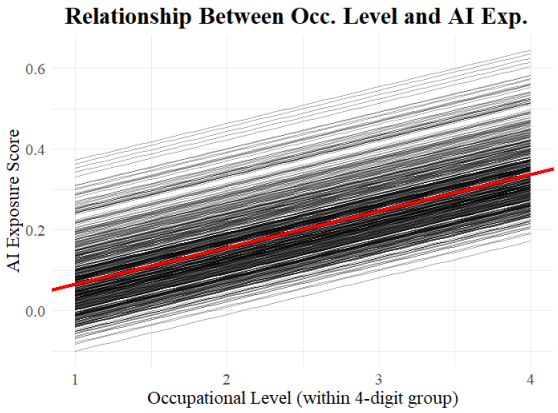


Figure 10: RIFS model AI exposure (own figure)

Second is the occupational impact on the *substitution score*, where the results show a significant impact of both the 4-digit occupation and the 5-digit skill level job. The effect between occupations (4 digits) is 0.075 (SE = 0.0076; t = 9.623; $p < 0.001$), which demonstrates a difference in substitution score can be explained by the 4-digit occupation a worker has. There is no direction to this effect, as occupations are just nominally scaled. Additionally, there is a significant link between substitution score and skill level with the effect being -0.019 (SE = 0.0026; t = −7.37; $p < 0.001$) within occupations. Therefore, an increase in skill level is associated with a decrease in substitution score. Overall, consequently there are differences in substitution score between occupations as well as within occupations. Both effects can also be seen in Figure 11. The difference between occupations can be seen through a wider spread of substitution scores along the intercepts and an obvious negative slope regarding skill level marks the difference between skill levels.

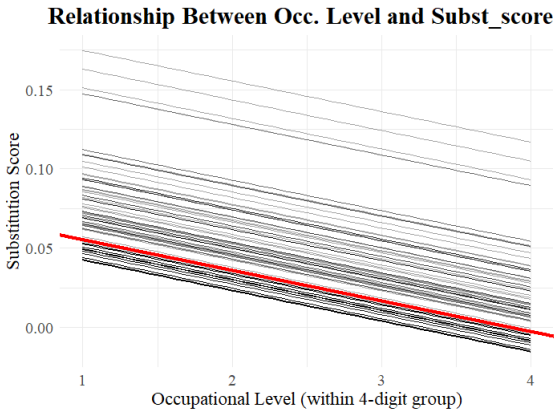


Figure 11: RIFS model substitution score (own figure)

Last, for the *complementarity score*, there again is both a significant difference of intercepts and for slope. The effect for different intercepts is 0.289 (SE = 0.022 t = 13.16; $p < 0.001$), reporting a significant difference in the baseline complementarity score between occupations on the 4-digit level. Further, there exists a positive within-occupation gradient by skill level. In this evaluation, the coefficient on skill level is 0.163 (SE = 0.007; t = 21.95; $p < 0.001$). So, within the same 4-digit occupation, moving from skill level 1 to level 4 is associated with an increase in complementarity of about 0.49 points. Thus, both – the occupation and skill level – of the job do have an impact on its complementarity score. This can again be seen in similar fashion as above in Figure 12.

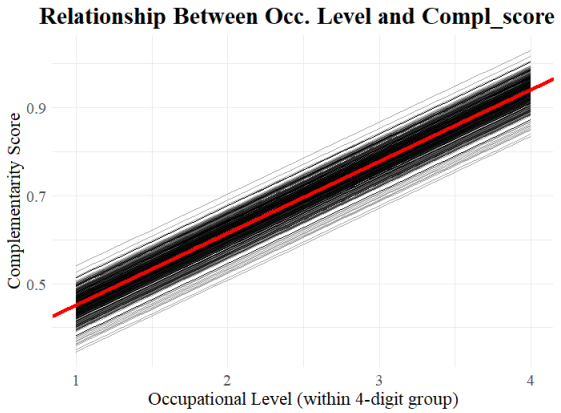


Figure 12: RIFS model complementarity score (own figure)

To conclude, for the three established variables: 1. AI exposure does not vary between occupations but does vary within occupations with higher-skilled jobs being more exposed to AI. 2. The substitution score depends both, on the occupation a worker is performing and the skill level at which he does, with higher skilled occupations having lower scores concerning substitution. 3. Complementarity is also different between occupations and increases with the skill level a job requires, such that higher-skilled jobs have got higher complementarity scores.

7.2.2 Impacts of AI Exposure, substitution score and complementarity score on employment

Now, impacts of AI Exposure, substitution score and complementarity score on employment are evaluated. For this analysis, the previously established dependent variables will now turn to explanatory variables. First, there will be an isolated report on general findings of these variables on employment in the forms of graphics like in Brynjolfsson, Chandar, and Chen (2025), before then using an OLS regression to numerically validate the significance of the observable impacts.

The first graph to look at is the employment trend from Q1 2020 to Q1 2025 with Employment indexed to Q3 2022 (the Quarter of Release of ChatGPT) regarding AI exposure. First, it becomes apparent that more exposed quartiles do have fewer periodical spikes, which usually are a result of seasonal labor. Second, it can be observed that all quartiles follow their trajectories independent of the shock moment. This would mean, there is no significant difference between pre- and post-shock trends.[33] Nevertheless, it is to be said, that apparently higher exposed jobs clearly have got greater gains in employment per quarter. As this does not change pre- and post-shock, there must be other factors, that result in greater growth rates for these jobs too.

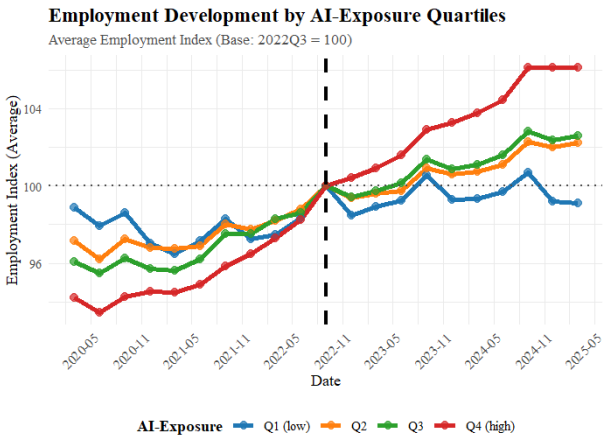


Figure 13: Employment trend by AI exposure quartiles (own figure)

When looking at the substitution score and employment trend from Q1 2020 to Q1 2025 (Figure 14), a similar pattern appears. Once again, there exist periodical spikes resembling seasonal tasks, like farming, but this time, no quartile is exempted from this trend. Second, again most graphs follow their pre-shock trend but there is a notable exemption, that becomes even more apparent when looking at the long-term trend in Figure 15, that starts in 2012. Both the lowest and the highest quartiles seem to be diverging

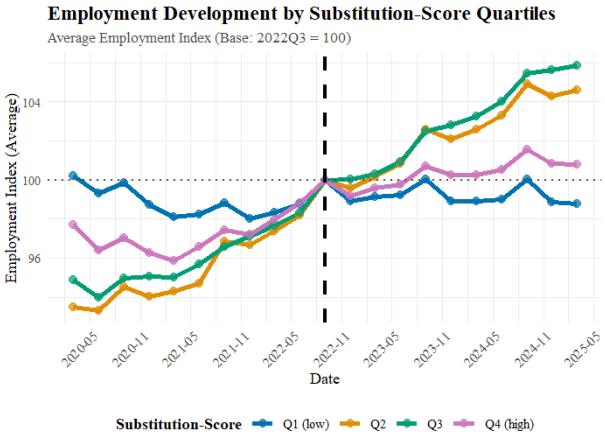


Figure 15: Employment trend by substitution score quartiles (own figure)

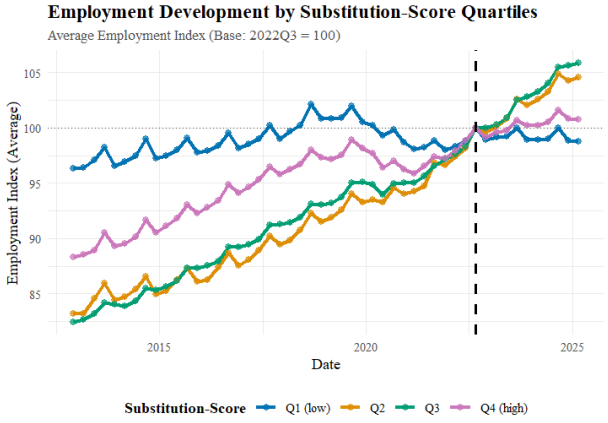


Figure 14: Employment development by substitution score quartiles 2012-2025 (own figure)

[33] Even when extending the graph to the full data-set (2012-2025), trends seem to be consistent throughout.

from their previous trends after the ChatGPT shock, even when considering the Covid-19 dip. Whether this effect is a coincidence or a reportable dynamic is tested using an OLS regression, whose results are displayed after the last graph.

The last graph (Figure 16) presents the employment trend from Q1 2020 to Q1 2025 with employment indexed to Q3 2022 regarding complementarity score Quartiles. Similarly to the previous graphs, periodical spikes are observable for all but the highly exposed quartile, reminding of a similarity to the AI exposure graph. Also like the AI exposure graph, trajectories of the quartile graphs do not seem to change depending on the shock. But a divergence of highly complemented and low complemented quartiles from the middle quartiles becomes apparent, that could resemble a kind of "hollowing out of the middle class".

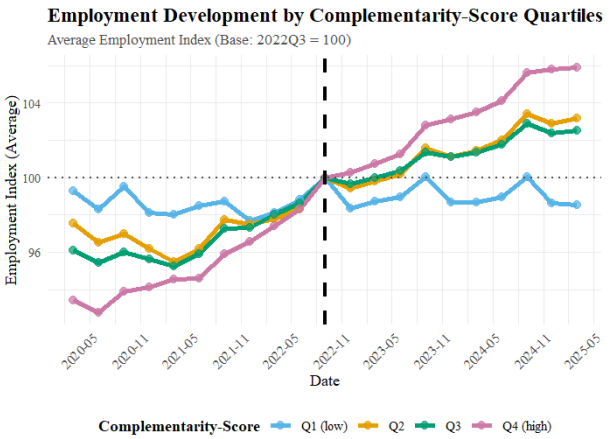


Figure 16: Employment trend by complementarity score quartiles (own figure)

7.2.3 OLS Regression testing 7.2.2

Now, to find out whether any of these three measures has a significant effect on employment, an OLS multiple regression model as described in the method section is used. This model has the lowest AIC out of the tried models. The results are presented in Table 9. The regression is of the form:

$$\Delta\text{employment}_i = \beta_1 \text{AIExp}_i + \beta_2 \text{Subst}_i + \beta_3 \text{Compl}_i + \varepsilon_i.$$

	Estimate	Standard Error	t-value	Pr (>|t|)
(Intercept)	-0.5149	0.6684	-0.770	0.44127
ai_exp	3.3796	1.1992	2.818	0.00493**
subst_score	-8.7680	2.8015	-3.130	0.00180**
compl_score	1.4619	0.9496	1.539	0.12401^{ns}
Significance: *** p<0.001 ** p<0.01 * p<0.05 ns=not significant				

Table 9: OLS regression results

The model explains approximately 3% of the variance in employment change (R^2 = 0.030, Adjusted R^2 = 0.027, F(3,993) = 10.30, p < 0.001), which is modest, but

considering the amount of possible cofounding variables in labor market scenarios, it is reasonable.

It can be reported that AI exposure and substitution score have a significant impact on the employment difference between the year prior to the ChatGPT shock and the year spanning Q2 2024 to Q1 2025. The effects are significant at the 1% level and point in two opposing directions. An increase in AI exposure score from 0 to 1 leads to an increase of employment by $\beta_1 = 3.38$ percentage points. As this effect is linear, an increase of AI exposure score by 0.1 increases employment by 0.34 percentage points. On the other hand, an increase of substitution score from 0 to 1 leads to a decrease of employment by $\beta_2 = 8.77$ percentage points and 0.88 percentage points for an increase of substitution score by 0.1. The evaluation shows that both AI exposure and substitution scores are valuable predictors concerning the dependent variable of employment.

To conclude this section, here is a brief summary of the steps taken, to obtain these results. By using an existing method of prompt-scoring to evaluate tasks based on their AI exposure, substitutability and complementarity on the German classification of occupations, this analysis showed patterns of between occupational and within occupational differences using a random intercept, fixed slope model and at last established a relationship between AI exposure, substitution score, complementarity score and changes in employment before and after the ChatGPT shock of November 2022.

How all these results fit into the previously presented theory and literature and how the hypotheses are to be evaluated will be the topic of the next section.

8 Discussion

8.1 Interpreting the results and hypothesis testing

The next section will build on the results of the previous section, combine them with theory and other empirical findings, to embed them in the current body of literature, support or reject the established hypotheses and give an answer to the research question.

Starting with the descriptive analysis and the general AI exposure of all tasks. A share of 28% of tasks having some form of AI exposure, fits perfectly to the value of 25% published by Goldman Sachs (Hatzius et al., 2023, p. 6), the score of 20% reported by Eloundou et al.(2024, p. 1309) and to the rates established by Chen et al. (2025).

Therefore, these values are reasonable and can be used for further analysis. Regarding values for substituting and complementing tasks through AI, results differ from those found by Chen et al. (2025), mainly because the German KldB 2010, version of 2020 is still based on 2010, which was long before the extensive era of Gen AI. Thus, it does not seem to contain many tasks that are connected directly to the development of AI (S1-tasks). Therefore the analysis only finds 0.39% of tasks falling in that category, whilst Chen et al. (2025) find 12.19% in the O*NET dataset of 2025. As there are no other scores to compare against for these values, the only other way of ensuring validity stems from manual labeling of tasks, which provides consistent results compared to the automated labelling. Thus, these results can also be seen as reasonable and can therefore be used as independent variables for the further analysis.

When comparing the lists of least and most exposed jobs in section 7.1 to AI's capabilities and the other rankings mentioned in section 4, most exposed to AI are indeed administrative occupations like public administration, sales and library occupations that perform tasks AI is capable of like logical reasoning and overall problem-solving as well as philological occupations including overall philologists, English and American philology experts and programming specialists with tasks like translating, text generation and coding that AI is also capable of. This result falls in line with most previous analyses (Brynjolfsson, Chandar, & Chen, 2025; Chen et al., 2025; Ellingrud et al., 2023; E. Felten et al., 2021; Georgieff, 2024; Handa et al., 2025; Hatzius et al., 2023). When looking for the least exposed jobs it becomes apparent that all jobs on the list of section 7.1 are typically performing manual work, which is in line with the analyses by Hatzius et al. (2023) and E. Felten et al. (2021) who also identify manual labor occupations as least exposed. Overall, the observed divide of exposed "white collar" jobs and unexposed "blue collar" jobs can be reinforced.

Additionally striking is the distribution of skill across the most and least exposed jobs, where 15 out of 16 least exposed jobs are considered low skill (level 1 and 2) and 9 out of 10 most exposed jobs are considered high skill (level 3 and 4). This is also reflected by the mean values of AI exposure, substitution score and complementarity score. There are linear trends for all three variables, finding higher AI exposure and complementarity for higher skill and higher substitutability for lower skill. By using an ANOVA as the first inferential statistics method, these trends are confirmed and statistically significant. Therefore, when analyzing the skill level at which a work is

performed (5th digit of Occ. ID), it can be stated that higher skill leads to higher AI exposure, higher complementarity and lower substitutability. Regarding exposure, this is in line with Toney and Flagg (2020) and E. Felten et al. (2021), that both find jobs requiring bachelor degrees more exposed to AI. The found result of Ernst et al. (2019) regarding higher complementarity for low-skilled workers and substitution for high-skilled workers was not found in this analysis and thus has to be questioned.

As the results of the ANOVA might misinterpret some results, additionally RIFS models provide insight into the true relationships between occupation, skill and AI exposure. The first analysis regarding AI exposure provides no significant difference between occupations on the 4-digit level, which is in line with the finding that in general previous literature has identified exposure effects for almost all industries and occupations. But the literature finds differences within occupations with higher-skilled jobs being more exposed. This is exactly what the results of this analysis show for the German labor market too. Exposure to AI increases with increased skill disregarding the baseline occupation a worker is in. Therefore, the first constructed hypothesis H1: "*Higher-skilled jobs show greater task-level exposure to AI than lower-skilled jobs*" is supported generally through the ANOVA and especially within occupations through the RIFS model.

When using the other two RIFS models regarding substitution score and complementarity score the analysis gives two results. First, for both variables, there are between occupation differences (4-digit level), indicating that some fields of occupations are more strongly substituted and complemented than others, which is in line with analyses mentioned above, that AI exposure in general is equally spread but the way in which it interacts with certain occupations is different. Which occupations are more substituted and complemented needs further analysis that cannot be performed using a RIFS model. But when comparing the dataset at hand with the findings by Chen et al. (2025), this work supports higher substitution scores of occupations regarding text work like translation and stenography in contrast to higher augmentation scores for engineering occupations that are also found by Dominski and Lee (2025). More important than between occupation substitution and complementarity score differences are the within occupation trends by skill. The results show, that higher-skilled jobs are more complemented by AI, which is convenient to previous findings and the theory. Both the task-based framework and the expertise model predict higher skilled labor to be more

complemented by AI. Similarly, when analyzing previous findings on productivity, high-skilled labor was seen by some as more complemented and benefitted through AI than low-skilled labor, although findings were ambiguous. This work gives support to the thesis formulated by Toner-Rodgers and Bae (2025), that AI complements skilled jobs, that can leverage the benefits of using it most effectively. Coming back to the theories by Acemoglu and Autor, they also predict higher substitution in jobs with lower skill, as technology is increasing on a linear scale, they argue, low-skilled labor is the first being replaced. This effect is found in the data at hand, as lower skill correlates with higher substitution scores within occupations. Therefore, workers in the same occupation working on different skill levels have different risks of being substituted. This is coherent with the theory of skill-biased technological change, which previously saw lower skilled workers being displaced first and is coherent with some of the studies above, that find younger, more inexperienced workers at greater risk of substitution (Brynjolfsson, Chandar, & Chen, 2025). When combining substitution and complementarity score, these results similarly to Lane and Saint-Martin (2021) show, that the impact of AI is different for high and low skilled workers, as low skilled workers may have their work replaced entirely when exposed, but higher skilled workers rather have their work changed and consequently, the second formulated hypothesis H2: "*Lower-skilled jobs face higher substitution risks, while higher-skilled jobs are more strongly complemented by AI*." can be supported.

Now that a difference in AI exposure, substitutability and complementarity has been established, it can be estimated that AI is truly an economy shaping technology that will alter a substantial number of jobs. Whether these effects are already visible in the German labor market is the last performed analysis that leads toward the last hypothesis. The trend analysis only showed hints at AI exposure and complementarity increasing employment with substitution not providing meaningful information. But the OLS model shows clears signs that AI exposure and substitution score are significant predictors of employment change pre and post ChatGPT shock. When jobs are highly exposed to AI, their employment generally rises and when they have greater substitution scores, their employment drops significantly. The complementarity score does not have a significant effect but is close ($p=0.12$) and would indicate rising employment. These findings align with the theory, as far as AI exposed jobs see automating and substituting effects but also expansions of the workforce if new tasks are added or

production is improved. By confirming that jobs with high substitution scores have seen decreases in employment, the automating effect of AI is already visible. Similarly, as the overall correlation of AI exposure and employment is positive, it seems that AI is generating new employment opportunities. As the complementarity score has no significant impact, it has to be estimated that increases in employment due to AI exposure do not stem from complementarity but rather new task creation. These results can be found in other literature too, as Chandar (2025) and Johnston and Makridis (2025) all find higher employment in more exposed jobs, but there are other findings by Dominski and Lee (2025) and Hampole et al. (2025) opposing increased employment. As mentioned in section 5.2 most other studies do not find any effects. Thus, significant effects on the German labor market add to the limited overall research but need to be confirmed in more work. Touching on the findings by Chen et al. (2025, p. 18) for the American labor market, that jobs with high substitution scores lose 18% of employment and jobs with high complementarity gain 22%, these results can not be confirmed, as the effect in this analysis is merely a drop by 8% for the substitution score and no significant change for the complementarity score. Overall, the effect of AI exposure, substitution score and complementarity score can be summarized like the following with regards to the third hypothesis H3: *Complementarity with AI is associated with positive employment outcomes, whereas substitution is associated with decreasing employment. The impact of exposure overall can go both ways*. The complementarity score is not a significant predictor of employment changes on the German labor market. A higher substitution score on the other hand does imply a decrease in employment when testing pre and post ChatGPT shock and last a higher AI exposure in general is associated with increases in employment for the job. The hypothesis can therefore be partially supported.

8.2 Limitations

When performing the empirical analyses some difficulties arose that can be seen as limitations. First, as AIs work on a probabilistic basis, when rating tasks using them, their results can be wrong. Additionally, all previous methods of using AI to evaluate tasks, used English descriptions of task from O*NET, which this work deliberately did not do. This language discrepancy might cause additional errors. Consequently, tasks might not be rated correctly. But by comparing 50 tasks manually and achieving high accordance, these issues are not likely to alter outcomes drastically.

Next is the analysis of data using a RIFS model with nested data with two predictors. As the structure of the dataset is highly complex, there might be more fitting models available to data scientists. As this is an economics master's thesis, the author used the "best" model according to the AIC that was available to him to provide results. An even more complex random intercept, random slope model might have yielded more accurate results but was not possible with the data at hand, therefore this model assumes that skill has the same effect within all occupations regarding the individual variables.

Next is an issue that arises for all analyses regarding substitution and complementarity by technology. As technology increases and complements more tasks, there is a point at which technology is able to outperform human workers and in turn substitutes. Thus, a high degree of complementarity might not be opposing to substitution but rather might be a step towards it. The author sees no way of fixing this issue even after extensive cooperative elaboration.

Another issue lies with employment data, as AI might be used as an excuse for layoffs in companies although they truly arise from different causes. This work has tried to work against this by analyzing the long-term trends of employment in the different quartiles regarding the variables but cannot account for all layoff reasons in the economy.

Last, it is also important to note that all results reflect the current, early stages of AI adoption (2022-2025) following the release of ChatGPT. The relative magnitudes and even directions of these effects may shift as AI technologies mature, diffuse more widely across the economy, and as labor markets adjust to their presence.

8.3 Answering the main research question

Although some limitations to this study's design remain, it provides the following answer to the main research question, asked at the very beginning of this thesis.[34]

[34] Answer to the sub-question: *How does skill level affect exposure to AI regarding task-level exposure, substitution and complementarity*? When considering individual job-based task descriptions, the values constructed are highly affected by both the 4-digit occupation and the skill level (5th digit). Higher-skilled jobs are generally more exposed to AI, are more complemented by AI and have lower substitution score. Thus, as for complementarity and substitution, skill-biased technological change is prone to repeat similarly to previous waves of automation.

The main research question *How does occupational exposure to Artificial Intelligence — measured through task-level exposure, substitution, and complementarity — affect employment outcomes across skill levels in the German labor market?* can be answered as follows. When considering that at least 28% of tasks are exposed to AI, it must be stated that AI is truly an economy shaping technology altering a substantial number of jobs. Especially since AI exposure is not one dimensional, but rather the combination of both between and within occupational differences in substitution and complementarity, dramatic shifts in the labor market must be expected but are difficult to predict. Distinctly important is the different AI exposure based on skill, where AI substitutes for low skill workers and complements high skill workers resulting in further skill-biased technological change and fostering the existing polarization of the workforce. These effects are not only expected to occur but are already visible in current German labor market data, that clearly indicates decreasing employment for jobs with high substitution scores. On the other hand, with an insignificant effect from complementarity but still rising employment for jobs that are exposed to AI in general, the conclusion can be made that currently new jobs created, that are exposed to AI, are outperforming the decrease in employment stemming from substitution.

9 Conclusion

The goal of this thesis was to establish a connection between task-based AI exposure, substitutability, complementarity and employment. Building on AI induced economic growth it became observable, that skill plays a vital part when translating technological change into employment, which resulted in using the task-based framework of occupations by Acemoglu & Restrepo (2024) and the expertise model by Autor (2025) as the basis to construct hypotheses about the interaction of AI exposure, skill and employment. By then analyzing current capabilities of AI and the heterogeneous usage and exposure, this work was able to identify the key mechanisms driving the current employment changes induced by AI. In that section, the thesis was able to develop occupational and skill differences that presumably predict how certain jobs are impacted by AI. Afterwards, related literature showed, that indeed AI is already shaping the labor market through productivity gains, changes in tasks and task assignment, where some early adopting industries allow for predictions for the rest of the labor market.

As all previously conducted research has used American labor market data and occupational classification, there exists a serious gap in transferring found labor market effects of AI to other economies, limiting external validity. Additionally, most studies do not focus on how AI exposure affects employment but rather that it does. These were the research gaps this thesis aimed to close. For this, it adapted a novel method using language based AI-using task rating to create job-level AI exposure, substitution and complementarity scores to evaluate the importance of skill in the age of AI and predict changes in employment for jobs. As a basis, it created a novel dataset regarding all jobs in the German Classification of Occupations 2010, which offers even more potential than what has been shown in this thesis and could be explored vastly in future publications.[35] Using this dataset, this thesis showed that using AI to analyze text-based descriptions of jobs is a viable option for German task descriptions that further research can use. Further possible research could examine already observable wage dynamics in the German economy, use qualitative studies to identify individual worker impacts of AI and whether these match the exposure found in this study. Additionally further research could try to replicate Autor's (2025) approach of using time series to observe changes in occupational task composition or test for differences between the private and public sector regarding AI integration.

For the performed analysis in this thesis, clear results can be stated. First, the analysis showed higher AI exposure and complementarity are given in higher-skilled jobs, whilst lower-skilled jobs are at greater risk of substitution. Additionally the results showed differences *between* occupations regarding complementarity and substitutability, albeit with no direction and *within* occupations for all tested variables. To evaluate, which certain sectors of the German economy are more prone to augmentation or automation, further research can build on this analysis and the scores established in this dataset. Further, the analysis provided insight into the employment effects of bespoke scores directly targeting the defined goal of this thesis. It established a connection of higher AI exposure to higher employment levels and higher substitution score to lower employment regarding the ChatGPT shock of November 2022. Overall, this thesis clearly states, that AI is reshaping the labor market and that effects are not one-dimensional and predictable but rather the combination of substitutive and complementary

[35] The possibilities of using the German classification of skills and combined German labor statistics opens opportunities for research, that is beyond the scope of this work. There are considerations with other research institutes, to evaluate the data further and publish a paper in the data science community.

effects between and within occupations. As for the fear of massive job displacement, this thesis has shown, that overall, AI has a positive impact on employment. Seemingly, for the analyzed timespan, new tasks created through AI have outperformed the number of jobs being directly substituted for. Thus, overall this thesis has provided useful insight into the transformation of the labor market by AI and how certain aspects will interplay.

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Appendix

A Wage analyses

A1 College Premium theory

As this thesis is examining the differences of highly skilled and unskilled workers regarding employment, at least a basic understanding of college premium theory is helpful. The college premium refers to the wage differential between workers with a college degree and those without one (Krusell et al., 2000, p. 1029). This premium arises from differences in skills and productivity, with higher-educated workers earning higher wages because they contribute more to output (Card, 2010). The size of the college premium is determined by the relative supply of and demand for skilled labor. Technological change plays a central role in shaping the college premium. When new technologies increase the demand for high-skilled labor relative to low-skilled labor, wages of college-educated workers rise, widening the college premium. This mechanism has been widely documented since the 1980s and is commonly attributed to skill-biased technological change, whereby technology complements educated workers while substituting for less-educated labor (D. Autor et al., 1997; Goldin & Katz, 1998, 2010).

A2 Bloom et al. (2025) model on college premium

Bloom et al.'s model is derived from a nested constant elasticity production function, similar to the formal version of D. Autor and Thompson (2025). Their goal is to find AI's impact on the college premium. As Bloom et al. identify the underlying issue of distinguishing changes in employment based on AI and based on robotization, they use a two-way split nested constant elasticity production function of unskilled (no bachelor) and skilled labor (with bachelor), with robots substituting unskilled labor and AI substituting skilled labor (Bloom et al., 2025, p. 3). At the same time, this is their main assumption: robots strictly substitute for unskilled labor and AI strictly substitutes for skilled labor (Bloom et al., 2025, p. 2). Through their production function, they can provide one elasticity per input, being able to establish ratios later. They formulate the following production function (Bloom et al., 2025, p. 3):

$$Y_t = K_t^{\alpha}\left[\beta_3\left(\beta_1 L_{u,t}^{\theta} + (1-\beta_1)P_t^{\theta}\right)^{\frac{\gamma}{\theta}} + (1-\beta_3)\left(\beta_2 L_{s,t}^{\varphi} + (1-\beta_2)G_t^{\varphi}\right)^{\frac{\gamma}{\varphi}}\right]^{\frac{1-\alpha}{\gamma}}$$

Here, Y_t is output in period t, K_t refers to traditional physical capital stock (assembly lines, machines), with α being its elasticity. β_1, β_2 and β_3 are input shares, $L_{u,t}$ is employment of unskilled workers, P_t the stock of operative robots and θ determines the elasticity between unskilled workers

and robots in unskilled intensive production tasks. $L_{s,t}$ denotes skilled worker's employment, G_t refers to the stock of AI replacing skilled labor, with φ being the elasticity of substituting skilled workers and AI in skilled labor intensive tasks. They do this to reflect task specialization of both groups of workers in a free market economy. Last, γ is the elasticity of substituting unskilled labor intensive production tasks with skill labor intensive production tasks. The reasoning here is that, if skilled workers are substituted by AI, firms might opt to expand skilled production at the cost of unskilled production. For all obtainable values, α, β_1, β_2, β_3, θ, φ and γ, they consider a reasonable range of $(0,1]$.

To evaluate the change in college premium, they now derive the production function two separate times. First, they obtain the unskilled wage rate $w_u = \frac{\partial Y_t}{\partial L_{u,t}}$ and the skilled wage rate $w_s = \frac{\partial Y_t}{\partial L_{s,t}}$, to then compute the skill premium as the factor by which the skilled wage rate exceeds the unskilled wage rate:

$$\frac{w_s}{w_u} = \frac{\beta_2(1-\beta_3)}{\beta_1\beta_3} L_{s,t}^{\varphi-1} L_{u,t}^{1-\theta}\left(\beta_1 L_{u,t}^{\theta} + (1-\beta_1)P_t^{\theta}\right)^{1-\frac{\gamma}{\theta}}\left(\beta_2 L_{s,t}^{\varphi} + (1-\beta_2)G_t^{\varphi}\right)^{\frac{\gamma}{\varphi}-1}$$

Rather than interpreting this expression in its entirety, this work skips to its G_t- derivative, as the change of $\frac{w_s}{w_u}$ due to AI change is the key object of interest here. Bloom et al. (2025) find $\frac{\partial(w_s/w_u)}{\partial G_t} < 1$,if γ < φ. That is, the college premium is decreasing if substituting skilled labor by AI is easier than substituting unskilled labor production tasks by skilled labor production tasks (Bloom et al., 2025, p. 3). If on the other hand φ < γ, the college premium will be increasing, as high skill labor will still be substituted by AI (φ > 0), but unskilled production in general will be substituted more strongly by skilled production resulting in a net wage loss for unskilled workers compared to skilled workers. In their analysis afterwards, Bloom et al. (2025) also vary the stock of robots but come to the same result.

To conclude, they argue, under the condition that AI strictly replaces skilled workers, the effects on the wage premium of skilled workers over unskilled workers is depending on the level of substitutability of skilled labor and AI, as well as the substitutability of skilled and unskilled production, as even with skilled labor being partially displaced, unskilled labor could be under threat of having its overall production displaced by skilled labor instead of individual jobs (Bloom et al., 2025, p. 3).

This model does not give any direct indication for employment effects, as quantities of labor supplied by each skill group ($L_{s,t}$ and $L_{u,t}$) do not respond to technological change in their model. Nonetheless, the projected dynamic can be kept in mind when analyzing employment changes.

A3 AI's impact on wages

First, there are several differing findings regarding AI's impact on wage and no clear effect direction can be made out. When analyzing previous waves of automation, it becomes apparent, that jobs, which are highly exposed to robots have experienced a decline in wages (Webb, 2019). Whether the same holds true for AI has been studied by many scholars with various findings. The most compelling argument has been made by Fossen and Sorgner (2019, p. 28) who establish a correlation of 11% and 14% for highly AI exposed jobs for men and women respectively. Furthermore, Jiang et al. (2025, p. 27) build a regression that yields an increase in wage by 0.25% per 1% increase in AI exposure and an increase in wage by 0.35% per 1% increase in AI net complementarity. Other Scholars also find increases in wages, either through productivity gains (Hartley et al., 2025, p. 10), higher demand for software skills (E. W. Felten et al., 2019, p. 1) or greater complexity of remaining job tasks (Georgieff, 2024, p. 13). Similarly, following up on the expertise model by D. Autor and Thompson (2025), AI induces changes in the composition of jobs by removing routine tasks or adding new unexposed tasks leads to rising wages for higher expertise jobs (D. Autor & Thompson, 2025, p. 49). Kogan et al. (2024, p. 36) show a rise in wages for jobs, where technology augments workers, which in turn increases labor demand. But they find this effect mainly for new entrants in these jobs and not incumbent workers. Humlum and Vestergaard (2025) only find "minimal effects on earnings" with regards to AI.

Opposing these views are a handful of scholars who find no significant change in wages with regards to AI. These include: Georgieff (2024), Brynjolfsson, Chandar, and Chen (2025), Fossen and Sorgner (2022) and Mäkelä and Stephany (2024a). Nevertheless, Georgieff (2024, p. 3) argues, there exists change in wage inequality within occupations. He mentions a converging wage trend within occupations that have higher AI exposure but no effect on inequality between occupations.

Other scholars point to differences based on demographic variables to explain changes in wage growth. Lane and Saint-Martin (2021, p. 27) find, that wage growth is mainly reserved for already high paying individuals, suggesting, they are better positioned to use AI and boost their productivity. On the other Hand, highly paid workers should experience larger declines in wages, as the

"drop" is greater, when some of their tasks are substituted (Fossen & Sorgner, 2019, p. 14). Nevertheless, E. Felten et al. (2021, p. 1) establish a link for AI Exposure and wage increases given higher-income jobs.

Alongside workers with already higher wages, some scholars find workers with higher education more benefitting from AI in terms of wages (Johnston & Makridis, 2025; Lane & Saint-Martin, 2021, p. 27), whilst Acemoglu (2024, p. 39) observes larger effects for workers with less than high school and other low educated workers. Last, Brynjolfsson, Chandar, and Chen (2025, p. 22) displayed, that in none of their analyzed occupational areas – software development, marketing and sales managers, first line production supervisors and health aides – did they find systematic wage changes through AI regarding age groups (Figure 17).

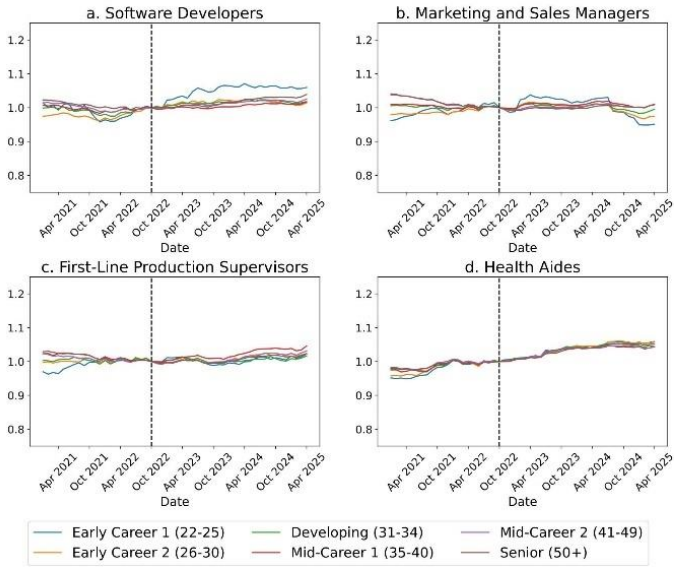


Figure 17: Changes in annual base compensation by age and occupation (Brynjolfsson, Chandar, & Chen, 2025, p. 22)

B Example of occupation (in German)

Die Berufsgruppe "1210_Berufe im Gartenbau (Ohne Spezialisierung)" teilt sich auf in die vier Berufe mit den jeweiligen Aufgaben:

1. 12101 Berufe im Gartenbau (Ohne Spezialisierung) – Helfer-/Anlerntätigkeiten:
- Fachkräfte im Gartenbau bei Bau, Gestaltung und Pflege von Außenanlagen unterstützen, z.B. bei Aushub, Verlege- und Pflasterarbeiten oder Anpflanzung von Rasen, Bäumen und Blumen
- eingehende Waren, wie z. B. Saatgut oder Düngemittel, entladen und sortieren
- Pflanzmaterial sowie Geräte und Baumaterialien transportieren, öffentliche und private Beete und Grünflächen zur Anpflanzung vorbereiten, pflegen und instand halten
- Boden mithilfe manueller Werkzeuge und einfacher Maschinen bearbeiten, Bäume und Sträucher roden, ballieren und verpacken
- einfache Reinigungs- und Lagerarbeiten ausführen
- Pflanzen pflegen, z. B. gießen oder schneiden und dekorativ kombinieren

2. 12102 Berufe Im Gartenbau (Ohne Spezialisierung) – Fachlich Ausgerichtete Tätigkeiten:

- Produktionsflächen anlegen, Gehölze, Gemüse, Obstbäume, Stauden oder Zierpflanzen vermehren, ziehen, ernten, lagern, vermarkten und versenden
- Grünflächen und Außenanlagen für Unternehmen, Gemeinden und für Privatpersonen anlegen und pflegen
- Maschinen und Geräte der Gartenbautechnik warten, kleinere Reparaturen vornehmen
- Kunden und Kundinnen zu Pflanzen und Grünanlagen beraten und betreuen
- Arbeitsabläufe organisieren, Mitarbeiter/innen anleiten
- Verwaltungsaufgaben und betriebswirtschaftliche Tätigkeiten im Gartenbaubetrieb übernehmen, z. B. Kostenrechnungen erstellen, Märkte beobachten, Kosten-Nutzen-Verhältnisse erfassen

3. 12103 Berufe im Gartenbau (Ohne Spezialisierung) – Komplexe Spezialistentätigkeiten

- Einkauf und Annahme, z. B. von Jungpflanzen oder Düngemittel, organisieren und überwachen, Qualität kontrollieren
- produktionstechnische Lösungen für Gartenbaubetriebe entwickeln und bei Anbau, Pflege, Ernährung und Vermehrung von Pflanzen umsetzen, Maßnahmen zum Pflanzenschutz entwickeln und umsetzen, Versuchsanbau durchführen
- effektive Ernte und optimale Lagerung über Faktoren wie Personal- und Maschineneinsatz, Temperaturregelung usw. steuern
- Produktionsmittel sowie technische Geräte und Einrichtungen rationell und umweltschonend einsetzen
- Kosten und Termine kalkulieren und deren Einhaltung kontrollieren
- Kontakte zu Kunden herstellen und pflegen, Kunden beraten
- die Einhaltung von Arbeits- und Umweltschutzbestimmungen überwachen

4. 12104 Berufe im Gartenbau (Ohne Spezialisierung) – Hoch Komplexe Tätigkeiten

- neue Verfahren und Methoden für Pflanzenzucht und Samenbau entwickeln
- an der Entwicklung und Optimierung von Anlagen und Maschinen für Anbau, Ernte und Verarbeitung von Gartenbauerzeugnissen mitarbeiten
- Versuche durchführen, z. B. hinsichtlich unterschiedlicher Substrate sowie Pflanzenschutz- und Düngungsmethoden
- in Gartenbaubetrieben die gärtnerische Produktion planen, leiten und überwachen
- Produktpalette an die Kundenwünsche anpassen, auf regionale Besonderheiten eingehen
- Gartenbaubetriebe beraten, z. B. zu Fragen der gärtnerischen Produktion, der Gartenbautechnik und des Einsatzes von Dünge- und Pflanzenschutzmitteln

- kommunale Träger bei der Durchführung von Maßnahmen unter dem Gesichtspunkt des modernen Gartenbaus und der Erhaltung der Natur bzw. des Umweltschutzes beraten

C1 Manual ranking of tasks to ensure validity

Task (one task per job, 50 random jobs out of 1298)	Manual scoring		ChatGPT Scoring	
38 Anlagen zur Fischzucht pflegen und instand halten, z. B. Wasserqualität prüfen, Ufer befestigen und begrünen	E0	S0	E0	S0
69 Kosten und Termine kalkulieren und deren Einhaltung kontrollieren	E2	S2	E2	S2
94 Erschließung von Lagerstätten sowie Gewinnung von Rohstoffen wie Kohle, Salze, Erze, Steine und Erden planen und koordinieren	E2	S2	E0	S2
190 Mitarbeiterschulung und -weiterbildung sowie den betrieblichen Teil der Ausbildung organisieren und durchführen	E2	S2	E2	S2
197 bei der Arbeitsprozessplanung und -vorbereitung mitwirken, Fertigungsprozesse optimieren	E2	S2	E0	S2
206 Arbeitsabläufe bei der Herstellung technischer Oberflächen mit hohen Anforderungen an Ebenheit, Genauigkeit und Schichtdicke planen, organisieren und überwachen, Qualität sicherstellen	E0	S2	E0	S2
217 feinwerktechnische Geräte und Systeme montieren	E0	S0	E0	S0
262 Ingenieurtätigkeiten in der Grundlagen- und angewandten Forschung auf dem Gebiet der Mechatronik übernehmen	E3	S2	E0	S2
299 Fertigungsprozesse einleiten, steuern, überwachen und optimieren	E2	S2	E2	S2
337 Grundsätze für das kaufmännische, personelle und technische Geschehen gestalten, die Geschäftspolitik bestimmen, künftige Betriebsstrategien entwickeln und festlegen	E1	S2	E1	S2
348 Produktionsaktivitäten in Bezug auf Produktionsqualität und -quantität detailliert planen, dabei Kosten, verfügbare Zeit und Arbeitsanforderungen beachten	E2	S2	E2	S2
354 Schaftteile zusammensteppen, Ziernähte anbringen, Kappen einarbeiten, Schäfte und Brandsohlen verbinden, Absätze anbringen, Laufsohlen montieren	E0	S0	E0	S0
358 über die Auswahl der Betriebsmittel entscheiden, Kostenfaktoren analysieren, beeinflussbare Kosten minimieren, Budgets überwachen, Betriebsabrechnung erstellen	E3	S2	E2	S2
363 Bier abfüllen, Fässer lagern und Reifestand kontrollieren	E0	S0	E0	S0
399 nach Vorgabe einfache Speisen vorbereiten, erwärmen, toasten und anrichten	E0	S0	E0	S0
400 Waren fachgerecht einlagern und Lagerbestände kontrollieren, z. B. Verfallsdaten überwachen, verdorbene Ware bzw. Ware mit abgelaufenem Verfallsdatum aussortieren	E0	S2	E0	S2
404 Gesichtspunkte des Natur- und Umweltschutzes beachten, z. B. regionale Produkte bzw. Produkte aus biologischer Erzeugung verwenden	E2	S2	E1	S2
422 Leistungsverzeichnisse bearbeiten und Angebots- und Preisvergleiche durchführen	E2	S3	E2	S2
426 mechanische, optische und elektronische Messgeräte bedienen	E0	S0	E0	S2
433 Baustellen einrichten, Absperrungen aufstellen, Geräte und Maschinen bereitstellen	E0	S0	E0	S0

435 Kalkulationen, z. B. Kosten von Baumaßnahmen oder zum Personal- und Maschinenbedarf, durchführen	E2	S2	E2	S2
442 Einbaubedingungen kontrollieren und ggf. Montageuntergründe ausbessern	E0	S0	E0	S2
452 Entwurfsunterlagen für Entwässerungsanlagen, Markierung und Beschilderung neuer Straßen und Wege ausarbeiten	E3	S2	E0	S2
478 bei feuchten Kellern Mauerwerke trocknen, dazu z. B. Belüftungen und Heißluftbehandlungen einsetzen	E0	S0	E0	S0
486 Skizzen bzw. Pläne anfertigen und auf dieser Grundlage Restaurationsarbeiten planen	E3	S2	E0	S2
561 Geräte und Versuchsaufbauten pflegen und instand halten	E0	S0	E0	S2
618 Anbindung von Computern an Telekommunikationsanlagen herstellen	E0	S2	E0	S2
640 die technische Überwachung von Installation, Instandhaltung und Reparatur der Maschinen und der Ausrüstung von Schiffen durchführen, um die Einhaltung von Spezifikationen und Regelungen sicherzustellen	E0	S0	E0	S2
693 Fahrgäste beim Ein- und Aussteigen und beim Umgang mit ihrem Gepäck unterstützen	E0	S0	E0	S0
698 Wettermeldungen überprüfen und Wetterlage beurteilen, Flugzeiten und Treibstoffbedarf berechnen	E0	S2	E0	S2
700 Flüge steuern, dabei die Systeme ordnungsgemäß und sachgerecht bedienen und präzise navigieren	E0	S0	E0	S0
708 Transportgeräte, wie z. B. Gabelstapler, Elektrokarren oder Hebevorrichtungen, bedienen	E0	S0	E0	S0
720 Auskünfte systematisch auswerten, Schrift- und Bildmaterial sichten, Ermittlungsberichte schreiben	E1	S3	E0	S2
725 Einsätze bei Unfällen oder Bränden, z. B. in einem Produktionsbetrieb, organisieren und koordinieren	E0	S2	E0	S2
793 den Verkaufsraum dekorieren, Waren ansprechend präsentieren	E0	S0	E0	S2
849 Konzepte zur umweltgerechten Betriebsführung ausarbeiten	E1	S2	E1	S2
867 Anfragen zu Problemen beantworten, beraten, informieren und Hilfeleistungen anbieten	E1	S2	E1	S2
873 Qualifikationsprofile für Bewerber/innen erstellen und mit den Stellenangeboten am Arbeitsmarkt abgleichen	E1	S2	E1	S2
898 Gewinn-, Verlust-, Bilanz-, Liquiditäts- und Investitionsrechnungen erstellen sowie Budgets aufstellen	E3	S2	E2	S2
925 Botengänge zwischen verschiedenen Abteilungen, Dienststellen oder Ämtern erledigen	E0	S0	E0	S0
929 im Grenzaufsichtsdienst und bei Abfertigungen im Reiseverkehr mithelfen	E0	S2	E0	S0
969 Röntgenaufnahmen erstellen, die der Diagnose von Erkrankungen sowie der Kontrolle des Behandlungsfortschritts dienen	E0	S0	E0	S0
1037 Maßnahmen der Grund- und Behandlungspflege bei pflegebedürftigen, älteren Menschen durchführen	E0	S0	E0	S0
1076 Kunden und Kundinnen hinsichtlich medizin-, orthopädie- oder rehatechnischer Geräte beraten	E2	S2	E0	S2
1093 das Budget festlegen und verwalten, Ausgaben kontrollieren und einen effizienten Ressourceneinsatz sicherstellen	E2	S2	E0	S2
1148 Textzeugnisse aus dem Altgriechischen, dem Lateinischen, dem Neugriechischen sowie dem byzantinischen Sprachraum analysieren, interpretieren und beschreiben	E3	S2	E0	S2
1177 Kommunikationsstrategien für Unternehmen, Institutionen oder Organisationen planen, entwickeln, implementieren und evaluieren	E2	S2	E2	S2

1208 Öl-, Acryl-, Aquarell-, Pastellgemälde nach eigenen Ideen oder Kundenwunsch anfertigen und restaurieren	E0	S0	E0	S2
1209 gedrechselte bzw. geschnitzte Werkstücke nachbehandeln, z. B. Oberflächen glätten, bemalen, lasieren, lackieren	E0	S0	E0	S0
1282 Mischpulte bedienen, Soundchecks durchführen, in Absprache mit Tonmeistern und Tonmeisterinnen Klangbilder gestalten, Lautstärken anpassen, technische Störungen nach Anweisung beseitigen oder überbrücken	E0	S0	E0	S2

Table 10: Maunal scoring of 50 tasks

C2 Example for scoring

12101 Berufe im Gartenbau (Ohne Spezialisierung) – Helfer-/Anlerntätigkeiten:

- Fachkräfte im Gartenbau bei Bau, Gestaltung und Pflege von Außenanlagen unterstützen, z.B. bei Aushub, Verlege- und Pflasterarbeiten oder Anpflanzung von Rasen, Bäumen und Blumen (E0,S0)
- eingehende Waren, wie z. B. Saatgut oder Düngemittel, entladen und sortieren(E0,S0)
- Pflanzmaterial sowie Geräte und Baumaterialien transportieren, öffentliche und private Beete und Grünflächen zur Anpflanzung vorbereiten, pflegen und instand halten(E0,S0)
- Boden mithilfe manueller Werkzeuge und einfacher Maschinen bearbeiten, Bäume und Sträucher roden, ballieren und verpacken(E0,S0)
- einfache Reinigungs- und Lagerarbeiten ausführen(E0,S0)
- Pflanzen pflegen, z. B. gießen oder schneiden und dekorativ kombinieren(E0,S0)

Exp_score: 6*0=0

Subst_Score=0, as so s3

Compl_Score=0, as no s2

D Prompts for AI exposure and substitution and complementarity score

```
You will be provided with a task, evaluate this task based on the
following framework and give an Exposure score, with reasoning of
the form "Score; Reasoning".

AI exposure score:

## E0 - No exposure:
```

Label tasks E0 if none of the above clearly decrease the time it takes for an experienced worker to complete the task with high quality by at least half. Some examples:

- If a task requires a high degree of human interaction (for example, inperson demonstrations) then it should be classified as E0.

- If a task requires precise measurements then it should be classified as E0.

- If a task requires reviewing visuals in detail then it should be classified as E0.

- If a task requires any use of a hand or walking then it should be classified as E0.

- Tools built on top of the LLM cannot make any decisions that might impact human livelihood (e.g.hiring, grading, etc.). If any part of the task involves collecting inputs to make a final decision (as opposed to analyzing data to inform a decision or make a recommendation) then it should be classified as E0. The LLM can make recommendations. - Even if tools built on top of the LLM can do a task, if using those tools would not save an experienced worker significant time completing the task, then it should be classified as E0.

- The LLM and systems built on top of it cannot do anything that legally requires a human to perform the task.

- If there is existing technology not powered by an LLM that is commonly used and can complete the task then you should mark the task E0 if using an LLM or LLM-powered tool will not further reduce the time to complete the task. When in doubt, you should default to E0.

E1 - Direct exposure:

Label tasks E1 if direct access to the LLM through an interface like ChatGPT or the OpenAI playground alone can reduce the time it

takes to complete the task with equivalent quality by at least half. This includes tasks that can be reduced to:

- Writing and transforming text and code according to complex instructions, - Providing edits to existing text or code following specifications, - Writing code that can help perform a task that used to be done by hand, - Translating text between languages,

- Summarizing medium-length documents,

- Providing feedback on documents,

- Answering questions about a document,

- Generating questions a user might want to ask about a document,

- Writing questions for an interview or assessment, - Writing and responding to emails, including ones that involve refuting information or engaging in a negotiation (but only if the negotiation is via written correspondence),

- Maintain records of written data, - Prepare training materials based on general knowledge, or

- Inform anyone of any information via any written or spoken medium.

E2 - Exposure by LLM-powered applications:

Label tasks E2 if having access to the LLM alone may not reduce the time it takes to complete the task by at least half, but it is easy to imagine additional software that could be developed on top of the LLM that would reduce the time it takes to complete the task by half. This software may include capabilities such as:

- Summarizing documents longer than 2000 words and answering questions about those documents,

- Retrieving up-to-date facts from the Internet and using those facts in combination with the LLM capabilities,

- Searching over an organization's existing knowledge, data, or documents and retrieving information,

- Retrieving highly specialized domain knowledge,

- Make recommendations given data or written input, - Analyze written information to inform decisions, - Prepare training materials based on highly specialized knowledge, - Provide counsel on issues, and

- Maintain complex databases.

E3 - Exposure given image capabilities:

Suppose you had access to both the LLM and a system that could view, caption, and create images as well as any systems powered by the LLM (those in E2 above). This system cannot take video as an input and it cannot produce video as an output. This system cannot accurately retrieve very detailed information from image inputs, such as measurements of dimensions within an image. Label tasks as E3 if there is a significant reduction in the time it takes to complete the task given access to a LLM and these image capabilities:

- Reading text from PDFs,

- Scanning images, or

- Creating or editing digital images according to instructions. The images can be realistic but they should not be detailed. The model can identify objects in the image but not relationships between those options

Here is the task:

GPT prompt for skill exposure score

You will be provided with a task, evaluate this task based on the following framework and give one skill score, with reasoning of the form "Score; Reasoning".

You are an expert in AI and technology skill analysis with a deep understanding of generative AI and its applications across various industries. Your task is to analyze a list of skills and classify each into

one of four categories:

1. "Gen AI Relevant Skill" (s1) - Software and technical skills directly related to the development, deployment, or application of generative AI

technologies.

Examples include: AI ChatBot, AI KIBIT, ANTLR, Apertium, Artificial Intelligence, Automatic Speech Recognition (ASR), Caffe Deep Learning Framework, Chatbot, Computational Linguistics, Computer Vision, Decision Trees, Deep Learning, Google Cloud Machine Learning Platform, Keras, Latent Dirichlet Allocation, Lexical Semantics, Machine Learning, Microsoft Cognitive Toolkit, MLPACK.

2. "Complemented by Gen AI" (s2) - Augmented skills that are "fundamentally human," but can be enhanced by generative AI tools. Examples include analytical thinking, problem solving, creativity, research, data visualization, strategic planning, predictive analysis, and rapid prototyping.

3. "Substituted by Gen AI" (s3) - Automated skills that will be entirely undertaken by generative AI, with minimal or no human interaction necessary. Examples include image and content generation, data sorting and categorization, forecasting, language translation, simple graphic design, and basic trend spotting.

4. "Irrelevant to Gen AI" (s0) - Limited impact skills that require a human touch, such as complex judgment or nuanced decision-making, that generative AI cannot accomplish. Examples include persuasion and negotiation, motivational leadership, ethical judgment and integrity, compassion, building human relationships, and physical

dexterity. In your classification, consider both the current state of generative AI and emerging trends that might influence the relevance of certain skills in the near future. Provide a classification code (s0, s1, s2, s3) and a brief justification for each classification.

Here is the task: