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AI in the Workplace: Who Is Using It and Why? A Look at the Driving Forces Behind Artificial Intelligence in German Companies

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***Abstract*—We examine the spread and usage of artificial intelligence (AI) in German companies. The study analyzes company characteristics that favor or inhibit the adoption of AI. Hypotheses are developed that include factors such as the type of job tasks, level of innovation, degree of digitalization, company size, and industry affiliation. Empirical quantitative data from the BIBB Training Panel shows that AI usage is slowly but steadily increasing, particularly in larger companies. The multivariate analysis highlights that an advanced digital infrastructure and an innovative corporate culture are crucial for the usage of AI applications. The findings aim to support political and business strategic decision-making processes and to promote the implementation of AI in companies while considering ethical considerations.**

***Index Terms*—Artificial Intelligence (AI), company level data, AI at the labor market, job tasks.**

I. Introduction

WHEN talking about technological transformation and digital technologies, artificial intelligence (AI) is of central importance, as it is a key technology for the digital transformation. The progressive integration of AI into the world of work supposedly marks an upheaval in the way companies operate and compete. The development of AI is not only a technical innovation, but also influences the structure of labor markets, the design of jobs and consequently, the qualification requirements for employees [1] - [4].

AI innovations have changed the perception on which job tasks are substitutable by technologies [1], [2]. In earlier work on changes in job tasks due to technology mostly routine manual tasks were labeled as substitutable [5]. Nowadays the debate also includes the possible substitutability of more complex or analytic tasks [6], as well as the emerging of new job tasks [1]. This shift in perception highlights the importance of analyzing the impact of digital technologies on the economy and society.

The fundamental difference between AI and other digital technologies is that AI technologies, particularly through the use of machine learning, focus on automating and optimizing tasks by learning from data, which can significantly enhance efficiency and decision-making in both physical and non-physical work processes. Deep learning is a subset of AI techniques that uses layered neural networks to analyze various levels of data.

So far, there is no clear definition of AI. AI is a collective term that is filled differently depending on the considered time period and technologies.

The concept of AI began with the first computers [7, pp. 529]. Creativity, self-improvement, and language use were quickly identified as important criteria for defining AI [8, p. 18]. In this sense, AI aims to mimic and replace human (job) tasks. The goal is to make problems mathematically computable. The term AI has been expanded through psychology, cognitive sciences, knowledge modelling, and expert systems to include learnable skills and competencies. Developing AI requires expertise in mathematics and computer science, as well as knowledge about the field the AI should be applied to [9]. In general, a distinction should be made between the development and the application of AI [10, p. 16]. The objective of this article is to examine the application and usage of AI in physical and non-physical work processes in companies and not the development of AI.

Despite the increasing presence of AI in discourses on the future of work, there is still relatively little empirically based knowledge about the spread of AI on the labor market and which specific types of companies actually utilize AI technologies. This is accompanied by a lack of knowledge about which company characteristics favor the adoption of AI and why. This research gap limits the understanding of how AI is used in companies as a tool to increase productivity and innovation, as well as how AI might change the company structures and the working conditions of employees.

Against this background, our study focuses on the question: Which company characteristics foster the use of AI? By answering this question, we aim to draw a differentiated picture of AI use in companies and to understand which factors pro-

The BIBB Qualification Panel is a study conducted by the German Federal Institute for Vocational Education and Training (BIBB). BIBB is a German federal institution under public law with legal capacity that is financed from German federal budget funds and is subject to the legal supervision of the Federal Ministry of Education and Research (BMBF).

mote or inhibit the integration of AI applications into everyday business life.

The relevance of this research arises from the rapid development and diffusion of AI technologies and their profound impact on the global economy and society. A comprehensive understanding of the operational use of AI in companies is crucial for shaping the future direction of labor market strategies, educational needs and technology policy measures.

Our findings could help to support political and strategic decision-making processes in companies, in order to utilize the potential of AI and to support companies on their way to implement AI applications in the work context while considering ethical considerations.

II. State of Research And Theoretical Background

The discussion (and the research) on the use of AI applications in the world of work has increased in recent years, particularly in light of the rapid developments in the field of machine learning and the associated potential for changing work processes. However, the discussion about AI is by no means new and dates back to the 1950s. Early research primarily focused on the technological foundations and theoretical possibilities of AI [11]. Over the years, interest has as well shifted to the practical implications of AI applications for the world of work, particularly in the context of digitalization [1], [3].

A major focus of current research, alongside the innovation of AI, is the substitutability of human labor by machine systems. Previous studies suggested that extensive displacement of human labor by technology is unlikely in the near future, even in advanced economies such as Germany [6], [12], [13]. However, the public discussion has taken a new direction, especially since the introduction of more advanced AI systems such as ChatGPT-3.5 at the end of 2022. Current debates emphasize that AI is increasingly able to take on more complex cognitive tasks, which were previously considered less automatable or substitutable [2], [14].

Empirical research on the spread of AI in companies shows that although the usage of AI applications is increasing, it remains overall at a relatively low level. According to the Mannheim Innovation Panel, the use of AI applications in manufacturing and business-related services was approximately 6 percent in 2019 [15]. Initial analyses from the BIBB Training Panel showed that only 3 to 4 percent of all companies in Germany used AI applications in 2019 and 2020 [3].

An employee survey from 2019 found that the non-use of AI applications in the workplace is declining, but that approximately 90 percent of employees still do not use AI applications or use them rarely [3].

The theoretical foundation of our analysis on the use of AI applications in German companies is based on the interplay of organization-specific characteristics and their reactions to technological innovations.

David Autor's and colleagues [5] research on the impact of technological change on the labor market, known as the task-based approach, which was later transformed to the concept of Routine-Biased Technological Change (RBTC) [16]. RBTC is a theory that assumes that technological innovations usually are able to replace programmable tasks which are referred to as routine and complement more analytic tasks. Manual tasks usually are not heavily affected by technologies.

According to the RBTC, this means that for companies, the decision to implement AI applications depends not only on the availability of the technology, but also on the types of tasks that exist in the company. Companies in sectors that are heavily characterized by routine tasks may be more inclined to use AI application to substitute certain tasks, while companies in sectors that require complex decision-making and human interaction may be more likely to use AI in a complementary way. Companies with more manual tasks might be less likely to use AI applications [2]. Moreover, advancements in AI have redefined the boundaries of replaceable tasks. So, as well certain complex and analytical tasks might be substitutable by AI.

In the following, on the basis of organizational theory and innovation economics [17] we developed hypotheses to explain the differences in the use of AI in companies according to certain company characteristics.

1. **Types of job tasks**

The type of tasks in a company influences the suitability of AI applications. Tasks that require analytical thinking and decision-making could be complemented and enhanced from AI, whereas routine tasks might be replaced by AI. Companies with a high degree of manual task should use AI less frequently. Therefore, we assume:

> **Hypothesis 1:** Companies whose activities require a high level of analytical and communication tasks as well as those with many routine tasks, use (or plan to use) AI more frequently than companies whose activities are mainly manual tasks.

2. **Level of innovation**

Companies that cultivate a culture of innovation and regularly introduce new products and services may be more willing to adopt AI applications. Thus:

> **Hypothesis 2:** Companies with a high degree of innovation are more inclined to use AI or plan to introduce it.

3. **Level of digitalization**

A higher degree of digitalization may indicate a greater willingness and ability to integrate AI applications, as existing digital systems can be more easily supplemented with new technologies. Therefore:

> **Hypothesis 3:** Companies with a higher level of digitalization are more likely to use or plan to use AI.

The importance of tasks and the potential for innovation and the level of digitalization must also always be considered in the context of economic resources and the institutional background of organizations. (Sociological) neo-institutionalism emphasizes the role of culture, social norms and education as driving forces behind the structure and behavior of organizations [17]. This approach can be used to explain differences in AI utilization based on cultural norms within different industrial sectors.

4. **Company size**

Larger companies generally have more resources and a greater capacity to spread risk, which enables them to adopt new technologies such as AI applications more quickly. Thus, we hypothesize:

Hypothesis 4: The larger a company is, the more likely it is to use or plan the use of AI.

5. **Industry-specific differences**

The applicability and benefits of AI applications vary greatly between different industries, depending on the specific requirements and technological maturity of the industry.

Hypothesis 5: Companies in technology-intensive sectors such as medical services and business-related services use AI (or plan to use AI) more frequently than companies in less technology-intensive sectors such as construction.

6. **Chamber membership**

Chamber membership can serve as a proxy for industry-specific norms and the degree of formalization of business practices. Companies in more modern and formally organized chambers may be more inclined to adopt new technologies. Additionally, companies affiliated with the chamber of crafts often perform tasks that require manual dexterity and are (so far) less replaceable by AI.

Hypothesis 6: Companies that belong to chambers of crafts are less likely to use AI.

III. Data Basis, Operationalization and Model

A. Data basis

The BIBB Training Panel, short for BIBB Establishment Panel on Training and Competence Development, forms the basis for analyzing the use of AI in German companies. The panel has been conducted annually since 2011 and is representative of all companies in Germany with at least one employee who subjects to social security contributions. It comprises a sample of at least 3,500 companies, with the number of companies surveyed varying between 3,500 and 4,000. The survey focuses on vocational education and training as well as continuing training and, since 2016, increasingly on digitalization in companies. Moreover, each year there are changing focus modules [18], [19]. For the descriptive results we use the waves 2020-2023, the multivariate analysis only focuses on the newest wave from 2023.

B. Operationalization

In order to measure and analyze the use of AI in companies, the variables were operationalized as follows for this study.

Dependent variable: AI utilization

As initially stated, AI is more than just deep learning and pattern recognition. However, our focus is data driven: To remain comprehensible to the broad range of companies in a general establishment survey, we use the term artificial intelligence and supplement it with typical but broad examples. AI utilization was measured using two items from a large item battery focusing on digital technology use in the company: Use of artificial intelligence and machine learning for 1) physical work processes (e.g. deep learning and pattern recognition in production, maintenance, building management or care); and 2) for non-physical work processes (e.g. deep learning and pattern recognition in marketing, procurement or human resources). In our question, we do not limit AI to deep learning and pattern recognition, but rather mention these as examples that are understandable and relevant to many companies.

The items were surveyed with three answer possibilities: 1) No, the technology is not currently being used in operations and there are no plans to purchase it. 2) No, the technology is not currently used in operations, but a purchase is planned. 3) Yes, the technology is currently being used in operations. The answers to both AI items were then combined to measure the overall use of AI in a company. For this we created a variable, with three categories: No AI use, if neither of the AI items are used (0), planed AI use, if at least one AI item is planned and none is used (1), active AI use, if at least one AI item is used (2).

Independent variables

The independent variables for the hypotheses are operationalized as follows:

- **Types of job tasks:** The survey asked about the frequency with which employees engage in job tasks categorized by the skill-level of their jobs: simple, medium, and highly skilled. Specifically, the tasks investigated included tasks that; a) where all details are prescribed, b) where involving repetitive processes down to the minutest details, c) require the use of tools or machinery, d) necessitate manual dexterity and craftsmanship, e) where involving informing or advising customers or patients, f) involve persuading others and negotiating compromises, g) where related to organizing processes or conducting research, h) improve or innovate procedures and processes.
  These tasks of all skill levels were grouped together and were then summarized into three dimensions using factor analysis: Routine tasks (a & b), dexterity (manual tasks; c & d) and communicative-analytical tasks (e, f, g & h).
- **Degree of innovation:** Recorded by asking about the introduction of new or significantly improved products or services in the last three years. The values are summarized in an index that reflects the degree of innovation: 0 = no innovations, 1 = improvements, 2 = new products, 3 = improvements and new products.
- **Level of digitalization**: In terms of digitization, companies were presented with a range of digital technologies that could be used in their operations. These technologies were added together to create a digitalization index ranging from 0 to 11. AI technologies were not included.
- **Company size:** Divided into four size categories: 1 to 19 employees, 20-99 employees, 100-199 employees and 200 and more employees. Employees in this case are only those, who are subjected to social security contributions.
- **Industries:** Eight categories: 1. Primary Sector (Agriculture/Mining/Energy), 2. Manufacturing, 3. Construction, 4. Trade and repair, 5. Business related services, 6. Other personal services, 7. Medical services, 8. Public services

and education. Those are based on the 2-digit NACE Rev. 2 classification but are summarized to only 8 categories.

- **Chamber affiliation:** Four categories, including no chamber (0), chamber of commerce and industry (1), chamber of crafts (2) and other chambers (3).

Additional control variables, which categorize the company environment, were included in the model:

- **Proportion of continuing training participants** Measures the proportion of employees (without apprentices) who have participated in continuing training measures in the past year (2022) financed by the employer (between 0 and 1).
- **Proportion of employees with simple task jobs:** Employees who carry out jobs that do not usually require vocational education and training (between 0-1).
- **Location:** Measures whether a company is located in Eastern (2) or Western Germany (1).
- **Training company:** Measures whether a company offer apprenticeships (1) or not (0).

C. Model

For the statistical analysis, an **ordered logit model**, which analyzes the probability of an ordered response variable, as it is the case for our dependent variable (No AI use (0), planned AI use (1) and active AI use (2)).

The ordered logit model is particularly suitable for analyzing ordinal response categories, as here the order of the categories is meaningful, but no equal distance between the categories is assumed. The model estimates the probability that an observation falls into a particular category or a lower category, given the explanatory variables. The coefficients in the model are interpreted as the change in the log odds of a higher category of the response variable when the explanatory variable is increased by one unit.

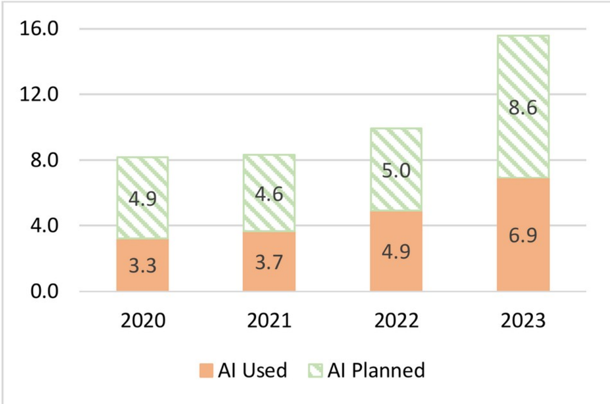
After estimating the ordered logit model, average marginal effects (AMEs) were calculated. These indicate the average change in the probability of the different AI application use categories when an independent variable is changing by one unit. AMEs provide a direct interpretation of the impact of the independent variables on the probability of each response category and are particularly useful for interpreting the results of a non-linear model such as the ordered logit.

IV. Results

D. Descriptive results

The descriptive analysis of the development of AI use in German companies from 2020 to 2023 shows a steady, albeit small, increase in both the actual use and the plans to implement AI technologies (cf. Fig. 1).

In 2020, 3.3% of companies actively used AI, while approximately 5% of companies planned to use AI in the near future. By 2021, the proportion of companies using AI had risen to 3.7%, while the proportion of companies planning to use AI remained roughly constant around 5%. A further increase was observed in 2022, with 4.9% of companies stating



Source: BIBB Training Panel 2019-2023, weighted data, n_{2020} =4,097, n_{2021} =3,981, n_{2022} =3,527, n_{2023} =3,002.

Fig. 1 Usage and planning of the use of AI by companies 2020 to 2023

that they use AI and still 5.0% planning to do so. A steeper increase in both use and planning can be seen for 2023. 6.9% of companies actually use AI, while now 8.6% state that they are planning to introduce AI. These figures illustrate that the willingness to integrate AI into business processes continues to grow. In the last four years, AI use in companies has doubled.

This increasing trend in the usage and planning of using AI applications could reflect a growing acceptance and confidence in AI technology, as well as the growing awareness of the benefits AI can offer in various business areas. The data also emphasizes the need to continuously monitor developments in the field of AI application, as rapid increases within four years are possible. Still, one has to keep in mind, that the spread of AI applications in German companies is still low, as only one in fourteen companies is using AI in 2023.

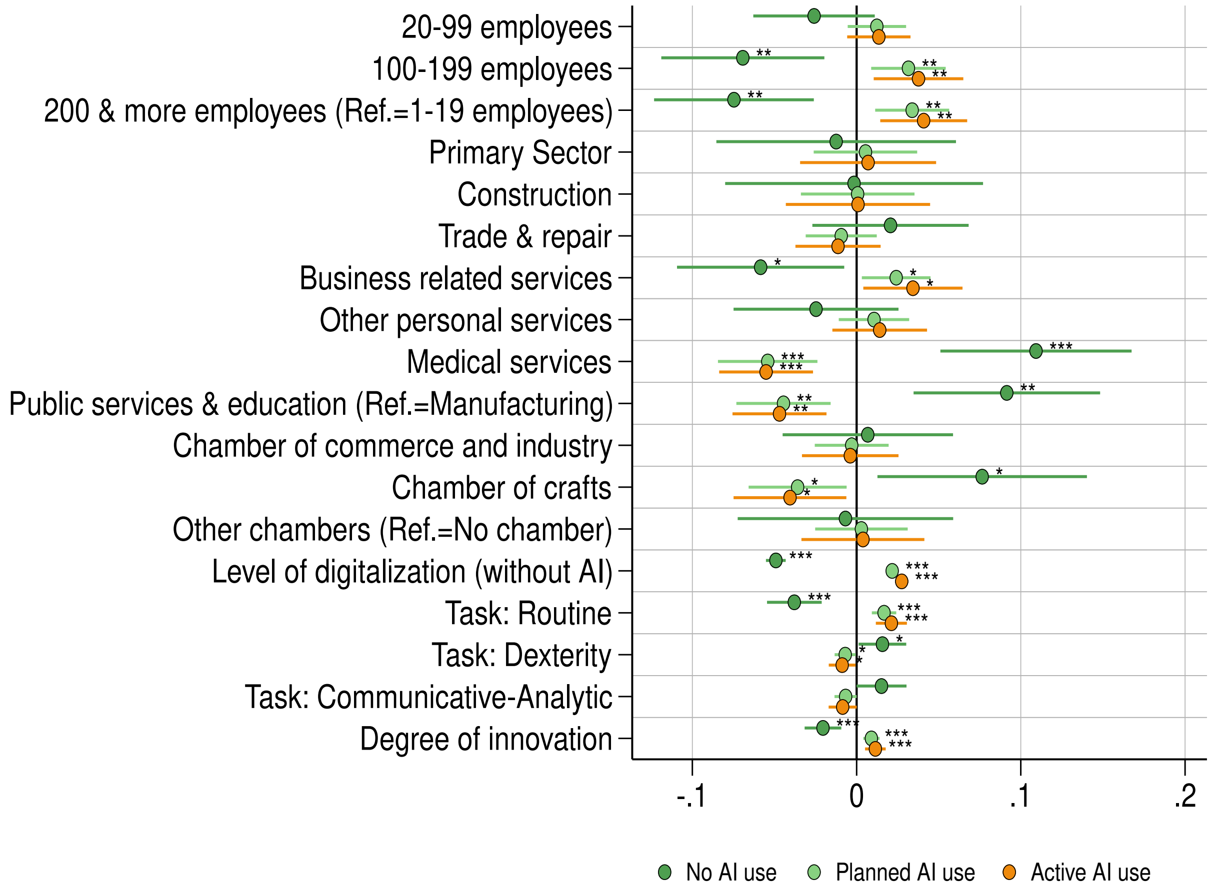
E. Multivariate results

The multivariate analysis of the use of AI applications in German companies in 2023 shows a clear differentiation according to company size, sector, chamber affiliation, level of digitalization, type of tasks and degree of innovation (cf. Fig. 2 and Table I). The analysis divides companies into those that use AI or plan to use AI, which show similar results, and those that do not use AI.

Types of tasks: Companies that require a high level of analytical and communication skills have a lower probability to use or plan to use AI. Though, this is not significant. This indicates that AI is not particularly used in areas where it can help to support complex decision-making processes.

In companies with a high level of routine tasks companies have a significantly higher probability to use and plan to use AI more often. Whether this means that those with routine tasks use AI more often and that AI complements their jobs or that companies with a lot of routine tasks use AI to substitute for such routine tasks must be explored in further research.

However, it appears that companies with a high level of tasks that are highly dexterous tend to have a lower probabil-



Source: BIBB Training Panel 2023, ordered logit model, n=3,002, Pseudo-R^2 = 0.1425. Average Marginal Effects (AMEs). ***>0.001, ** > 0.01, *>0.05. Also controlled for are: Training company (yes/no), Proportion of continuing training participants, Proportion of employees with simple task jobs and location in West or East Germany. Ref. = Reference Category. The entire model, including control variables, is listed in the appendix.

Fig. 2 AI use in German companies in 2023 according to company structure characteristics

ity of using AI applications. As well their probability of planning to use AI is lower.

Degree of innovation: Companies that have a high degree of innovation have a higher probability of using AI as well as of planning to use AI

Level of digitalization without AI: Companies that have a high level of technology use (level of digitalization without AI) also have a higher probability of using or planning on using AI applications. This could emphasize the importance of an existing digital infrastructure as a basis for the introduction of more advanced technologies such as AI.

Company size: Larger companies (200+ employees and 100-199 employees) show a higher probability to use or to plan the use of AI compared to smaller companies (1-19 employees). This suggests economies of scale effects and larger pools of resources in large companies, that favor the introduction of AI.

Industry-specific differences: Industries such as business-related services have a higher probability to use and plan AI applications in comparison to manufacturing. In contrast, the probability for medical services and public services and education are lower for using or planning to use AI applications. AI. For the other sectors no significant differences arise. This reflects the different digitalization potentials and needs of the sectors.

Chamber membership: Companies that are members of the chamber of crafts have a lower probability to use or plan the use of AI compared to companies without a chamber. This could be due to the more traditional business models and processes in many manual tasks. There are no significant differences for the other chambers.

V. Conclusion

Descriptively, our data show that the use of AI in German companies is slowly but steadily increasing. The results of the multivariate analysis demonstrate that company size, sector, level of digitalization and degree of innovation are important predictors of AI use. Moreover, the results emphasize the types of job tasks within a company as fundamental for the introduction of AI.

In summary, the following hypotheses cannot be rejected:

- H2: Companies with a high degree of innovation are more likely to use or plan to use AI.
- H3: A higher degree of digitalization of a company correlates with a higher probability of AI use or the planning of it.
- H4: Larger companies are more likely to use or plan to use AI.
- H6: Companies that are members of chambers of crafts are less likely to use AI.

Against H1 companies with a high intensity of communicative-analytic tasks show a negative albeit non-significant correlation with the probability of using or the planning of using AI. However, in accordance with H1 companies with a high level of routine tasks use or plane to use AI more often. Companies with a high level of dexterity tasks seem to use AI less often. So, H1 only has to be (partly) rejected. Companies, whose activities require a high level of routine tasks use AI more frequently, while companies with a high level of dexterity tasks use less AI.

For H5 we see an ambiguous picture. Most sectors are not significantly different in their AI use in comparison to manufacturing. In comparison to manufacturing, public services and education have a lower probability of AI use or planning of it, while business related services have a higher probability of AI use or planning of it. These results fit to the hypothesis that companies in technology-intensive sectors use (or plan to use) AI more frequently than those in less technology-intensive sectors.

However, as well medical services show a lower probability of AI use ore planning of it in comparison to manufacturing. This seems to be against H5 as certain branches of the medicine field seem to be technology-intense. An explanation might be the heterogeneity of this sector, as it as well incorporates smaller medical practices (e.g. general practitioners) and nursing services. Also, the results just indicate lower probability in comparison to manufacturing and not a generally low use. Still, H5 cannot be fully accepted.

Our findings build on the existing state of research and expand our understanding of where AI is being used in German companies. Previous quantitative studies for Germany have shown that the adoption of AI in companies is progressing but remains at a relatively low level [3], [15]. Our research supports these findings and provides detailed insights into the company characteristics that correlate with AI use, emphasizing in particular the role of job tasks next to structural company characteristics. Further research should explore those finding more in depth and as well could focus more on the (adaption) processes within the companies with quantitative as well as qualitative data (e.g. in-depth interviews, observations).

A limitation of the study is the restriction to quantitatively recordable data at the company level, which does not consider the subjective perceptions and attitudes of the interviewed decision-makers as well as their knowledge about the usage of AI in all company areas or by all employees (e.g. usage of AI software by employees without official introduction by the company). This might lead to respondent biases and potential inconsistencies in the reporting across different companies. A further limitation is that the measurement of AI is somewhat approximate and may not be fully comprehensible to all interviewees, nor does it encompass all applications that fall within the definition of AI. In addition, the dynamics of the AI market are so fast that the data can quickly become outdated, which limits the generalizability of the results.

The results of this study offer starting points for future research that could deal with the implementation of AI in specific industrial contexts or with the effects of AI on the quality of work. As well, these results could be mirrored with qualitative data, to gain deeper insights in the workplace use of AI and the factors affecting AI use.

For policymakers, the findings can provide a basis for formulating guidelines that could promote a broader and more effective use of AI in the German economy, within ethical limits. The application of AI should be used to improve human working conditions and enrich their job tasks and not lead to displacement of jobs or worsening working conditions (e.g. more routine tasks, surveillance, clock or click work). Moreover, privacy and security concerns should be acknowledged in this regard and AI should not be used for extensive surveillance of the employees. Furthermore, it is not uncommon for biases and discriminatory patterns to be embedded in the training data. It is imperative that such biases are identified and subsequently avoided, as they have the potential to influence crucial decisions such as hiring or performance assessments.

The application of AI in the workplace and in society gives rise to a number of further ethical concerns. These include the need for transparency and accountability in AI systems, which may be perceived as opaque and unaccountable (i.e. AI as a black box). There is also a need to establish ownership of AI-created work, and to consider the potential for manipulation and misinformation through the use of AI (i.e. deep fakes).

In practice, companies can use the results of this analysis to enhance their strategic planning with regard to the introduction of AI technologies.

In the context of digital transformation and its impact on society and the economy, the findings of this study emphasize the necessity to proactively shape technological change and complement it with tailored education and labor market strategies in order to fully capitalize on the benefits of AI while minimizing potential risks for employees and society as a whole.

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APPENDIX

TABLE I:
RESULTS OF THE ORDINAL REGRESSION

	No AI use	Planned AI use	Active AI use
1 - 19 employees	Ref.	Ref.	Ref.
20 - 99 employees	-0.026	0.012	0.014
100 - 199 employees	-0.069**	0.032**	0.038**
200 & more employees	-0.075**	0.034**	0.041**
Primary Sector	-0.012	0.005	0.007
Manufacturing	Ref.	Ref.	Ref.
Construction	-0.002	0.001	0.001
Trade & repair	0.021	-0.009	-0.011
Business related services	-0.058*	0.024*	0.034*
Other personal services	-0.025	0.011	0.014
Medical services	0.109***	-0.054***	-0.055***
Public services & education	0.091**	-0.045**	-0.047**
No chamber	Ref.	Ref.	Ref.
Chamber of commerce and industry	0.007	-0.003	-0.004
Chamber of crafts	0.076*	-0.036*	-0.041*
Other chambers	-0.007	0.003	0.004
Level of digitalization (without AI)	-0.049***	0.022***	0.027***
Task: Routine	-0.038***	0.017***	0.021***
Task: Dexterity	0.016*	-0.007*	-0.009*
Task: Communicative-Analytic	0.015	-0.007	-0.008
Degree of innovation	-0.020***	0.009***	0.011***
Proportion of continuing training participants	0.036	-0.016	-0.02
Proportion of employees with simple task jobs	-0.010	0.004	0.006
Location: Eastern Germany	-0.008	0.003	0.004
Training company	0.011	-0.005	-0.006
N	3,002	3,002	3,002
R^2	0.1425	0.1425	0.1425

Notes: Ordered logit model. n = 3,002. Pseudo-R^2 = 0.1425. Average Marginal Effects (AMEs). ***>0.001, ** > 0.01, *>0.05.
Ref. = Reference Category. Source: BIBB Training Panel 2023

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