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Do We Need Explainable AI in Companies? Investigation of Challenges, Expectations, and Chances from Employees' Perspective

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Abstract

By using AI, companies want to improve their business success and innovation chances. However, in doing so, they (companies and their employees) are faced with new requirements. In particular, legal regulations call for transparency and comprehensibility of AI systems. The field of XAI deals with these issues. Currently, the results are mostly obtained in lab studies, while the transfer to real-world applications is lacking. This includes considering employees' needs and attributes, which may differ from end-users in the lab. Therefore, this project report paper provides initial insights into employees' specific needs and attitudes towards (X)AI. For this, the results of a project's online survey are reported that investigate two employees' perspectives (i.e., company level and employee level) on (X)AI to create a holistic view of challenges, risks, and needs of employees. Our findings suggest that AI and XAI are well-known terms perceived as important for employees. This is a first step for XAI to be a potential driver to foster the successful usage of AI by providing transparent and comprehensible insights into AI technologies. To benefit from (X)AI technologies, supportive employees on the management level are valuable catalysts. This work contributes to the ongoing demand for XAI research to develop human-centered and domain-specific XAI designs.

***K*eywords** Explainable AI · Human-Centered AI · User Evaluation

1 Introduction

AI applications have already impacted our private and our work life, e.g. voice recognition in smartphones or web-based language translators. National and international companies are aware of the impact of AI technology on their success and innovation potential. For example, companies in Europe expect a sales increase with the help of AI of about 5 million US-Dollar until the year 2025 [1]. At the same time, legal regulations are demanding more and more that these AI technologies need to be comprehensible and transparent[1]. However, these requirements are not inherent, for example in deep neural networks (DNN), often referred to as *black-box models*.

The research area of Explainable AI (XAI) has dedicated itself to close this gap and provide comprehensible explanations of black-box AI systems. Gunning et al. [2] see the motivation of XAI in providing comprehensible explanations to humans. In the context of DNN, this means that it becomes explainable when its inner workings or decisions are described and explained so that humans can understand it [3]. Besides this, researchers claim more and more that *one explanation does not fit all*, and demand that XAI needs to be personalized, depending on the stakeholder and the application scenario [4, 5]. The popular opinion is that XAI has different relevance for different stakeholders [6]. Therefore, Schneider and Handali [6] highlight the importance to collect and investigate data of explainees.

[1]e.g., the *AI Act* of the European Commission https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52021PC0206

The overview of Langer et al. [7] show that most of the scientific work in the field of XAI is done without empirical investigation of users. The small amount of conducted experiments investigates the impact of explanations on users in different domains such as healthcare (e.g., [8]), education (e.g., [9]), and production work (e.g., [10]). These research works primarily focus on laboratory experiments and give first impressions and understandings about the impact of XAI on users, referred to as *human-grounded evaluation* [11]. The insights of these lab-studies show that users' attributes and the characteristics of the AI application have to be taken into account when designing XAI [12]. Nevertheless, lab studies neglect the demands of real-world applications. Kraus et al. [13] investigated the impact of XAI in economically relevant ecosystems (e.g., healthcare, financial and manufacturing sector, construction industry). For this, they conducted an online survey and interviews with relevant stakeholders. The focus of their work lies especially in the investigation of the helpfulness of different XAI tools for application-specific use-cases. However, the needs and attributes of stakeholders have also to be taken into account when designing XAI [14]. Regarding company employees', needs and attitudes regarding (X)AI are still unclear. Our project paper approaches this issue by asking employees about their attitudes towards (X)AI and their impressions of AI deployment in the company they work for. Therefore, our paper investigates two employees' perspectives of (X)AI by using an online survey: (1) the employees' company perspective including an overview of the current AI applications used as well as (2) the personal perception of employees towards AI and XAI. More concrete, this paper contributes the following:

- It provides employees' views about their companies usage of AI technology and their perception of XAI
- It gives an overview about challenges and risks of AI technology that employees perceive and provides impressions of users' needs
- Finally, it concludes *lessons learned* that help researchers investigate human-centered XAI designs in the domain of companies and industry

2 Online Survey

The focus of the online survey is on identifying the actual state of (X)AI-related issues and potential in companies. To achieve this, employees of companies of different sizes and sectors were asked about AI technology's current and future development in their company by means of an online survey.

2.1 Research Questions

We asked each employee about the current status as well as the strategic planning of the use of AI systems in their company. For this, we formulated the questions of the survey from two perspectives: (1) a broader *company perspective* and (2) a *perspective of employees* working in these companies[2]. Due to the fact that we want to investigate employees personal perspective as they are interacting with a (future) AI system in the company, it is important to note that the company perspective reflects the employees' subjective perception and not the companies' slogan.

Employees' Company Perspective The company perspective may generally serve companies that do not yet, hardly or already use AI technologies for further strategic orientation and planning. For example, what are company motivations, usage areas, or issues? Here, the experiences and decisions gained from the current state help assess the individual potential by introducing or using (X)AI technologies. In order to inquire the company perspective, that is the view of employees about AI in their company, including a look at the existing AI applications and those planned for future, we formulated the following research questions:

- **RQ-C1**: What motivations and risks for their company do employees see in using AI technologies?
- **RQ-C2**: Do companies already use AI technology, and if so, which applications exist in companies?
- **RQ-C3**: What are companies' plans regarding the use of AI technologies?

Employees' Personal Perspective Insights from the general attitude, knowledge, or acceptance of (X)AI technologies, including demographics, from the perspective of employees show the state of practical implementation in companies. For example, this provides guidance for improvements or what to look for when implementing AI technologies. To investigate the personal perception of employees regarding (X)AI and their experiences with AI technologies in their companies, we formulated the following research questions:

- **RQ-E1**: How do employees rate their (X)AI knowledge and attitudes towards (X)AI?
- **RQ-E2**: How do employees rate the AI technologies used in their company?

[2]Abbreviation interpretation of the research questions: RQ = research question, E = Employee, C = Company

- **RQ-E3**: Is there a correlation between personal AI knowledge/attitude and the rating of AI technologies in the company?
- **RQ-E4**: How does the perception of the AI technology used in their company differ depending on demographic data (e.g., age, educational attainment, company position)?
- **RQ-E5**: How is the knowledge and attitude towards XAI related to demographic data?

2.2 Methodology

We derived a questionnaire with groups of questions addressing each of our formulated research questions and distributed the questionnaire as an online survey through multipliers of the *Plattform Lernende Systeme/ acatech* (e.g., chambers, competence centers, corporate leaders) to cover a broad portfolio of companies and their employees. The questionnaire was in German and addressed employees of German-based companies. In this project report, we focus especially at employees with experience or knowledge of AI technologies in their companies in order to obtain valid results.

Demographic Data We collected information of participants about their age, gender, educational background, knowledge and their role in the company. In addition, we investigated their knowledge and attitude about (X)AI and their rating of importance of XAI for different stakeholders (7-point Likert scale). While AI is a broad area including a variety of different methods, we presented participants a more general definition of AI: "The term 'artificial intelligence' is often used to describe machines (or computers) that mimic 'cognitive' functions that humans associate with the human mind, such as "learning" and "problem solving". This definition is oriented on the definitions given by Russell and Norvig [15]. Due to an expected heterogeneous pool of company employees we choose a broad definition of AI to verify that participants had a general understanding of AI. In later questions, they had the chance to describe the specific AI systems that are used in their companies. XAI was described by highlighting the goal of it [16]: "Explainable AI will enable people to understand, appropriately trust, and effectively manage AI technologies."

Company Information To get an overview of the size and domain of the company, we asked questions about the sector and in which area (i.e., production or office work) the participants work. Here we used a combination of predefined answers and free-form answers.

AI Technology - Strategy To investigate the strategic plans towards AI for the company, we asked about future plans of the usage of AI (e.g., "In which areas do your company plan to make changes with the help of artificial intelligence in the next years?"). Furthermore, we addressed chances (i.e., "What is driving AI development in your company?") as well as risks (i.e., "What are challenges, obstacles or problems for your company in the implementation of AI?"). For each question, we gave predefined answer options and the possibility to write free text answers.

AI Technology - Usage Here, we requested detailed information about the AI technologies used (i.e., task/ goal of the AI, field of application, autonomy of the AI, duration of use). In addition, we asked, inspired by the overview of XAI metrics of Hoffman et al. [17], five items on a 7-point Likert scale (1 = not at all, 7 = extremely), regarding on the AI technology's reliability, usefulness, transparency, operablility, and comprehensibility.

Training Offers We investigated general and AI-specific training offers of companies. The analyses, results, and discussion of these investigations were published in [18].

2.3 Participants & Companies

We collected data from 50 participants between 25 and 66 years (M = 45.0, SD = 11.3). Thirty-four of the participants were male, 16 female. 80% of them had an academic educational background (i.e., bachelor/master degree or higher). 24% were employed in medium-sized, 56% in big-sized companies. Here, 84% had a domain expert role, scientific expert role, or leading position. Workers and temporary staff were with 16% barely represented.

3 Results

3.1 Results of Employees' Company Perspective

RQ-C1 to RQ-C3 The strongest *motivation of companies* for using AI technology is an increase in productivity (n = 23), followed by an increase in flexibility (n = 21), customer requirements (n = 18), and adjustment of business models (n = 18). *Risks* by using AI are financial aspects (n = 24), qualification of employees (n = 21), and acceptance by employees (n = 18). 56.8% of the participants stated that their company uses AI technology in prototypes (12 companies) or applications on a daily basis (13 companies). Furthermore, AI technology has been used in 54.2% of the companies for more than two years. More details were revealed by the free-form answers about the *application areas of AI*. Here, we found four clusters:

Table 1: Rating of AI technology used in companies on five items. A one-sample t-test revealed that all items were perceived significantly positive by employees.

Rating item	$t(22)$	p	d
useful	5.79	$< .001$**	1.21
reliable	2.87	.009*	0.60
operable	2.60	.016*	0.54
comprehensible	3.88	$< .001$**	0.81
transparent	2.43	.024**	0.51

*$p < .05$, **$p < .001$

- **Quality Assurance**: Mostly, participants stated that the AI technologies used helped monitor and predict the quality in production (e.g., by predictive maintenance using image classification), which assures the quality of the produced goods or the functioning of the machines used.
- **Process Optimization**: Due to streamlining of processes (e.g., by automatically evaluating and clustering Big Data), processes are optimized. This leads to a cost reduction due to shorter and more efficient processes.
- **Support Employees**: AI is also used to support employees in fulfilling their tasks successfully, especially in office work. The usage of AI here covers a broad spectrum, from a simplification of bookkeeping to support of office-based work processes (e.g., software as a service[3])
- **Interaction & Communication**: This includes the communication with customers or employees by means of chatbots (e.g., check-in process of a guest in a hotel) as well as interaction in the form of robots within a physical environment (e.g., intelligent positioning where a robot pick up goods).

For the *future*, participants stated that their companies focus on the usage of AI to change processes within the organization (n = 29), followed by the goal of developing new technologies (n = 25), and changes in the organization of the company (n = 21). Although, we have a small sample of employees, the clusters found for AI applications (e.g., process optimization), as well as the risks (e.g., qualification of employees) seen in the use of AI in companies, are very similar to the results of larger surveys from over 500 industry companies in Germany [20, 21].

3.2 Results of Employees' Personal Perspective

RQ-E1 All of the participants have heard of the term "artificial intelligence". 87% of them agreed to our given definition of AI. Five participants had a different definition of AI in mind, especially focusing on "the cloud" rather than on physical machines or indicating that the term "AI imitates human behavior" is not correct to them. 62.5% of the participants had heard about the term XAI, while 37.5% did not. Participants found XAI relevant for all the interest groups queried (items ranged from 1 = not important to 7 = very important), especially for companies (M = 6.05, SD = 1.41) and politicians (M = 5.90, SD = 1.50).

Conducting a one-sample t-test, we found that participants had a significantly positive view towards AI compared to the mean value of the rating scale (i.e., M = 4, 7-point Likert scale), $t(39)$ = 7.92, p = $<$ .001, d = 1.25 (large effect)[4].

RQ-E2 Employees rated their experience with AI technology in the company significantly positive compared to the mean of the rating scale (i.e., M = 4, 7-point Likert scale) (see Table 1) for the items comprehensibility, transparency, reliability, usefulness, and operability (see Figure 1).

RQ-E3 We found a significant positive correlation[5] between employees' attitude towards AI and their rating of the AI technology in their company, $r_{sp} = .71$, $p < .001$, meaning that the higher the personal attitude towards AI of the employees, the higher is their positive perception of the AI technology in their company. The same significant positive relationship was found for the employees' attitude towards XAI and their rating on their company's AI technology, $r_{sp} = .56$, $p = .007$.

RQ-E4 and RQ-E5 Demographic attributes such as age, gender, and educational background of employees did not correlate with the perception of AI technology in their companies, but with their *role in the company*, $r_{sp} =$.-61,

[3]Buxmann et al. [19, p.500] describe the usage of the software as a service:"customers are provided with a standard software solution as a service via the Internet."

[4]The effect size d is calculated according to Cohen [22]. Interpretation of the effect size is: $d < .5$: small effect; d = 0.5-0.8 : medium effect; $d > 0.8$: large effect

[5]We calculated Spearmans' Rang correlations

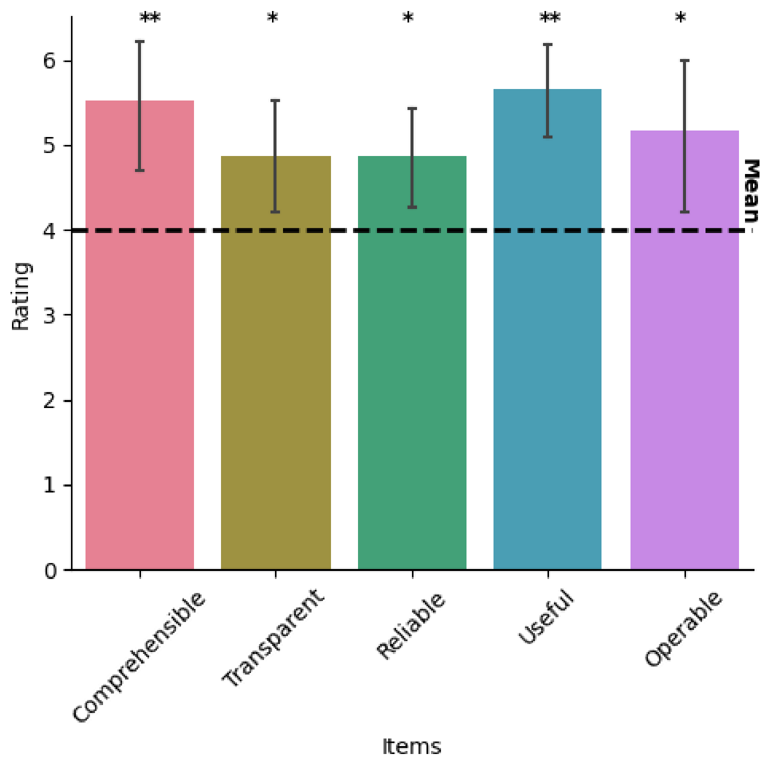

Figure 1: Rating of the AI technologies used in companies by employees. Employees perceived the AI technology significantly positive, compared to the mean of the rating scale, *$p < .05$, **$p < .001$. Error bars represent the 95% CI.

$p = .003$. This indicates that participants with a higher position in the company perceived the AI technology as less favorable.

The knowledge about XAI correlates positively with educational background, $r_{sp} = .53$, $p < .001$. Regarding XAI attitude, the demographic attributes *company role*, $r_{sp} =$ -.42, $p = .008$, and *educational background*, $r_{sp} = .38$, $p = .015$ showed a significant correlation. These correlations indicate, similar to the perception of AI in the company, that a higher position in the companies leads to a less positive attitude towards AI while the educational background seems to impact the knowledge as well as the attitude towards XAI positively.

4 Lessons Learned

Based on the results of our online survey, we report lessons learned that should be taken into account when designing and evaluating XAI for companies:

Convince Management and Promote (X)AI Education We found a correlation between employees' attitude towards AI and their rating of AI technology used in the company, but no correlation of this rating with demographic data except for company role. Each participant responded for the company level as well as the employee level, so no correlation or a negative correlation represents a clear indicator of need for improvement of the implementation of AI technologies. For XAI, we found that the knowledge and the attitude about XAI depend on the educational background and the company position of the employees. These findings are similar to the ones of Weitz et al. [9] who found that demographic information such as age and gender have no impact on users' perception of (X)AI in an educational setting, but the educational background has an impact on the trustworthiness of the AI system. Hence, it is highly worthwhile to create and foster a positive attitude towards AI from the very beginning, especially in the leading management, in order to achieve appropriate trust and a successful usage of deployed AI technologies later on. Appropriate trust refers to a trust in a technical system that matches the true capabilities of it [23]. Since it is one of the goals of XAI to support appropriate trust in AI technology [17], trainings that include XAI techniques could be the key.

XAI is Known and an Important Issue XAI is already a known term for many employees, which is contrary to findings of earlier studies (e.g., [24]). This indicates that company employees are more in touch with the problem of explainability and are aware that this is an important topic. As also reflected in the ratings, XAI is considered necessary, especially for companies. This awareness represents a fruitful basis for developing XAI for real-world applications.

Companies Should Address the Goal of XAI Our results also suggest that AI technology is perceived as already comprehensible and transparent among our respondents. Nevertheless, the training of employees regarding AI is seen as a challenge for companies as we reported in [18]. Based on the same survey data, we found in [18], that AI usage leads to increasing requirements of employees. With these results, the question arises whether and when XAI should be used in companies. We can imagine two possibilities for XAI usage: (1) XAI that serve especially in supporting employees in their actual tasks. Here, XAI's goal is to provide good explanations supporting people in their work (e.g., diagnosis of malfunctioning parts). (2) XAI can be used for the training of employees, for example to explain the inner workings of AI (in training) to help employees work successfully with it by understanding it better, i.e., gaining AI competence. In addition, XAI can help reduce fears towards AI technology that employees may have. Overall, to identify concrete goals of XAI in companies, further studies have to investigate in more detail, which and to what extend XAI methods are used in the company.

It is Necessary to Address All Employee Groups In general, we found that employees perceive the company's AI technologies as comprehensible, transparent, reliable, useful, and operable. While these results are encouraging, it is essential to note that we have responses almost exclusively from employees with an academic background and are leaders or have domain expertise. Therefore, it remains unclear whether employees with other backgrounds have similar impressions. Thus, for further studies on XAI in companies, special attention should be paid to reaching other target groups such as workers and untrained staff who operate with AI. In addition, by recruiting participants via the Plattform Lernende Systeme, a selection bias [25], leading to responses especially from people interested in the topic and therefore having a more positive view towards (X)AI could be possible.

5 Conclusion

The elevation of company success and innovation through AI is one reason why companies address AI in their strategic plans. Legal regulations force them to have comprehensible AI systems. XAI refers to methods that address this issue. While research is just starting to investigate the impact of XAI on end-users in lab experiments, real-world applications are not the focus of investigation right now. To design and evaluate XAI for companies, the perceptions and needs of employees should be given attention to use AI in a human-centered way. Our conducted online survey has moved research one step closer to this goal by investigating employees' perspectives towards X(AI). Our findings in this project report suggest that fostering a positive attitude of AI on the management level is an important step for the successful integration of AI technologies in companies. XAI is already a known topic for employees and perceived as an important issue. With our insights we encourage researchers in including attitudes of employees towards (X)AI in their design to create a more human-centered XAI.

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