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Opportunities and risks for employees arising from the use of generative AI tools in German companies – A systematic literature analysis on human-machine interaction in everyday working life

Master's degree in Business Informatics

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Abstract

Generative AI tools such as ChatGPT and Copilot are noticeably changing work processes in German companies. This thesis examines the opportunities and risks arising from everyday human-AI interaction from the perspective of employees. Based on a systematic literature analysis (PRISMA-oriented), peer-reviewed studies and practical case reports are evaluated, focusing on three areas of application: customer communication, software development and data analysis.

The results show substantial efficiency gains (including automation of repetitive tasks, faster knowledge work, shorter feedback loops) alongside increasing control and validation requirements and a greater need for domain knowledge. Key risk axes are hallucinations and bias, data protection/compliance uncertainties, increased cognitive load due to multitasking and context switching, and skill shifts between upskilling/reskilling and de-skilling. Theoretically, the findings are framed by, among other things, the job demands-resources model, technology acceptance (TAM/UTAUT), human-AI teaming, and skill-biased technological change.

The study derives three courses of action from the findings. These are: consistent further training with a focus on critical thinking, data/AI skills and effective prompting; participatory governance with clear guidelines, co-determination and privacy by design; and human-in-the-loop processes as the standard for quality-sensitive tasks, including traceable responsibilities and auditability. This allows the potential for increasing added value to be exploited without incurring additional burdens and risks in connection with compliance.

Limitations relate to the dynamic evidence base and the lack of primary data collection; field experiments, mixed-method studies and longitudinal designs are recommended to assess the effectiveness of the measures on quality, productivity and health.

Keywords: *Generative AI (ChatGPT, Copilot); employee perspective; customer communication; software development; data analysis; human-in-the-loop; data protection & compliance.*

Abstract

Generative AI tools such as ChatGPT and Copilot are visibly reshaping work processes in German companies. This thesis examines, from the employees' perspective, the opportunities and risks arising in everyday human–AI interaction. Based on a systematic literature review (PRISMA-oriented), it synthesises peer-reviewed studies and practice-oriented case reports, focusing on three application domains: customer communication, software development, and data analysis. The findings indicate substantial efficiency gains (e.g., automation of repetitive tasks, faster knowledge work, shorter feedback loops) alongside rising requirements for control and validation as well as for domain expertise. Key risk axes include hallucinations and bias, data protection/compliance uncertainties, increased cognitive load due to multitasking and context switching, and competency shifts between upskilling/reskilling and de-skilling. The results are theoretically framed by the Job Demands–Resources model, technology acceptance (TAM/UTAUT), human–AI teaming, and skill-biased technological change. From these findings, the thesis derives three lines of action: continuous training focused on critical thinking, data/AI competencies, and effective prompting; participatory governance with clear policies, co-determination, and privacy-by-design; and human-in-the-loop processes as the default for quality-sensitive tasks, including traceable accountabilities and auditability. In this way, organisations can leverage the productivity potential without externalising additional burdens or compliance-related risks.

Limitations concern the dynamic evidence base and the absence of primary data collection; future research should include field experiments and mixed methods as well as longitudinal designs to assess the effects of these measures on quality, productivity, and employee health.

Keywords: Generative AI (ChatGPT, Copilot); employee perspective; customer communication; software development; data analysis; human-in-the-loop; data protection & compliance.

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1. Introduction

Generative artificial intelligence (AI) has been part of the digital transformation in German companies for several years. Applications such as ChatGPT and Copilot are currently changing the face of business processes and tasks in numerous industries and are an important topic in science and practice. The use of generative AI tools, which enable the generation of text, images, audio tracks or videos on command, among other things, is also a current topic of research discourse. Concrete opportunities and risks are being debated in this context.

In particular, the focus is on the impact these applications will have on employees in German companies. Bias and hallucinations, data protection and compliance, efficiency and cognitive load, upskilling/reskilling and de-skilling, as well as autonomy and control are challenges that discussed . The starting point for this work is based on scientific findings that show that the use of generative AI can contribute to increasing efficiency and effectiveness, simplifying and designing workflows, and facilitating time-consuming, repetitive routine tasks. However, findings also show that the introduction of generative AI tools brings with it challenges in terms of ethical, occupational psychological and regulatory aspects. Furthermore, the results of studies make it clear that the introduction of generative AI places higher demands on human-machine interaction. This applies, for example, to error checking and critical reflection on AI-generated content.

Research also shows that the current state of research does not yet sufficiently take into account the perspective of employees in the implementation of generative AI. However, employee acceptance, trust and competence development are key factors in the effective use of generative AI tools.

The aim of this thesis is to identify the opportunities and risks associated with the use of generative AI in German companies from the perspective of employees. The focus is on the aforementioned problem areas, which pose a challenge for German companies and need to be examined closely in terms of their impact on employees. This is based on the following research question: "What opportunities and risks arise for employees in German companies from the use of generative AI tools such as ChatGPT or Copilot – and how do these affect everyday work in human-machine interaction?" The presentation and subsequent discussion of the opportunities and risks of using generative AI in German companies from an employee perspective is only addressed sporadically in research

This work addresses this by examining the specific effects on employees. The work will answer the research question with a systematic literature analysis. Studies, empirical investigations and practice-oriented case studies will be reviewed and evaluated, and the results will be summarised in a systematic and transparent procedure. Specific search criteria such as empiricism, topicality, practical relevance and employee perspective will be used to ensure that the selected sources are relevant to the respective problems. Furthermore, the results will be interpreted on a theoretical basis and recommendations for action will ultimately be derived. The aim is to highlight both the positive opportunities in terms of increased efficiency and the risks. These risks include higher cognitive load, loss of control, data protection issues and de-skilling through the use of generative AI for employees in German companies.

Following this introduction in Chapter 1, Chapter 2 explains the theoretical foundations of generative AI and relevant models of human-machine interaction in a business context. Chapter 3 discusses the methodology of systematic literature analysis. Chapter 4 presents the core findings of the study on the problem areas of bias, data protection and compliance, efficiency and cognitive load, upskilling/reskilling and de-skilling, and autonomy and control. These findings are then summarised and analysed in Chapter 5 and linked to existing theories, ultimately leading to the development of concrete recommendations for continuing education management, AI governance and human-in-the-loop models. Chapter 6 summarises the findings of the study once again and provides a conclusion with an outlook on future research projects and areas for action.

1.1 Problem

The use of generative AI tools such as ChatGPT and Copilot in everyday German business life is perceived as a great opportunity on the one hand, but also as a challenge on the other.

A key problem is the lack of reliability of AI outputs. Algorithmic bias and hallucinations can lead to incorrect decisions and pose a potential threat to work processes and employee trust in these technologies.

In this context, Hubel et al. (2024), Huchler et al. (2020) and Krieger et al. (2025), for example, come to the following conclusion. This could lead to a decline in acceptance and use in the medium to long term. Due to negative experiences, this technology could be underutilised and its potential benefits could not fully exploited .

Empirical studies on generative AI applications show, for example, that in some cases the AI outputs need to be controlled. This highlights the uncertainties associated with the use of generative AI. Hallucinations and other errors have been repeatedly described in the literature; therefore, generated content should always be validated (Majkovic et al., 2024; Siebert, 2024). Hallucinations are particularly critical when they play a role in business processes, as they are difficult to detect. Control is therefore mandatory , to avoid serious consequences .

The fact that outputs must be checked and adapted changes the role of employees: they go from being consumers to controllers of AI output. For this reason, new skills and responsibilities must be learned, as employees take on more responsibility (Huchler et al., 2020; Krieger et al., 2025). Employees can advance to strategic positions, but at the same time, control means more work and responsibility. Without appropriate training, this can lead to excessive demands and to a reduction in work motivation . Studies describe how faulty AI output leads to a significant loss of trust and results in a poor working atmosphere and a lack of motivation. . . (Hubel et al., 2024). These findings are supported by examples, as generative AI causes a certain degree of reluctance among employees. This makes it clear that employees and the use of AI need to be better managed in order to avoid mistrust, motivate and promote innovation. Reduced use of generative AI systems can lead to increased competitive pressure, higher costs and greater demands on companies. The lack of rules and training, as well as the neglect of data protection and compliance issues, lead to major data protection problems in the context of the use of generative AI . Numerous employees circumvent authorisation processes and use their private accounts (Krieger et al., 2025; Henke, 2023). This quickly puts companies in grey areas that fall outside the scope of the GDPR and can encourage misuse. Krieger et al. (2025) state that over half of knowledge workers in Germany, the USA and the UK use generative AI applications without having permission from their company. Data protection violations, damage to the company's image and high fines can be the consequences .

Despite extensive discussions about generative AI tools in companies and strong demand, only a few organisations have issued application guidelines to date (Henke, 2023).

Most companies have not yet issued official rules for the use of AI tools. Accordingly, there is a need for governance and awareness formats. Due to a lack of training for employees, they lack the skills and awareness to use the technologies in a manner that complies with data protection laws. This results in misconduct and circumvention of regulations, as well as non-compliance with rules. The resulting liability risks for companies further reinforce the need to develop guidelines and awareness measures for the use of generative AI applications.

The ambivalence of using generative AI in terms of time savings and workload is controversially discussed in scientific literature. Henke (2023) and Hubel et al. (2024) emphasise that the technology saves time and offers considerable benefits. Above all, the networking of processes can lead to significant time savings and improvements in work-life balance. The contrast between relief and mental strain is evident in the increased multitasking and technical difficulties associated with AI tools, as well as the high level of control required. In the long term, this can lead to a reduction in concentration and mental overload. By taking over simple tasks such as document creation, essential resources are saved and freed up for more complex, creative and entrepreneurial value-adding tasks. On the other hand, there is the obligation to monitor, which also takes up time and mental resources. In his empirical study, Löll (2024) concludes that Generation Z in particular experiences the contradictions of simplification and work intensification. According to his findings, routine tasks can be accelerated, but at the same time, the effort required for monitoring and validation must be managed and motivation to always be at the cutting edge of technology must be maintained (Majkovic et al., 2024; Hubel et al., 2024).

The cognitive load in the workplace with regard to the use of generative AI tools is characterised by greater task diversity and faster context switching, which makes it difficult to maintain focus on each task. The search for sources of error and their correction bring additional difficulties. Against this background, the entire field of work organisation and stress management needs to be fundamentally redesigned in order to support people in their daily working lives with the help of technology (Henke, 2023).

The use of generative AI tools also leads to a redistribution of skills. New skill requirements arise from the control of AI, the evaluation of AI results, monitoring and data management (Hubel et al., 2024; Krieger et al., 2025). On the other hand, working with generative AI tools can lead to a loss of skills if areas of activity that are important for ensuring operational processes and the survival of the company are neglected and experiential knowledge is gradually lost

lost (Reinmann, 2024). (Reinmann, 2023). Therefore, upskilling and reskilling must strike a balance between competence-related stress and underchallenge. The level of competence should be continuously monitored and controlled to ensure a balanced training programme. Training courses should place greater emphasis on developing meta-skills, such as critical thinking and problem solving (Körner et al., 2019).

In summary, it can be said that a considered and well-thought-out human-machine interaction between humans and machines must be developed so that humans can responsibly integrate generative AI into work processes in the future. They become "accomplices", i.e. partners for companies, so that they remain viable in the long term (Aldendorff & Löhe, 2025; Huchler et al., 2020).

1.2 Objectives and research questions

Given current developments in AI, it is crucial to systematically analyse the opportunities and risks of generative AI tools from an employee perspective. Generative AI tools such as ChatGPT and Copilot have been proven to increase efficiency and reduce the workload in everyday working life. However, it is important to note that these efficiency gains are offset by negative aspects. The most significant challenges in this context include increased cognitive load, loss of trust due to distortions and hallucinations, and the risk of data protection violations or compliance breaches. The literature suggests that, in the majority of cases, these challenges have a significant influence on how generative AI is perceived and used. The trust gap in these tools is also substantiated by studies such as those by Hubel et al. (2024) and Majkovic et al. (2024). These studies show that the results of AI tools had to be checked by employees. These perspectives show that the employee perspective is a field of research that needs to be given more attention. Current studies tend to focus on organisational and technological factors, which is why the critical weighing of the opportunities and risks of generative AI should be a necessary component of future studies.

Another challenge is the use of AI tools, taking into account legal and ethical implications. Recent studies show that employees often use generative AI via private accounts, while binding company guidelines are still rare (Krieger et al., 2025). This creates risks in terms of data protection and GDPR compliance, as company data is processed outside the intended control mechanisms

. This challenge highlights the need for companies to develop clear guidelines for the use of generative AI. Henke (2023) also points out that few companies have implemented governance approaches to date – a critical shortcoming given the risk of unauthorised tool use. Further research and organisational development are therefore needed to ensure the sustainable and meaningful use of generative AI.

Another challenge is the development of skills within the company through generative AI. The literature shows that the application of this technology leads to changes in skills development. The review of AI results, the understanding and evaluation of the responses of generative AI, and the consideration of data protection aspects are increasing (Hubel et al., 2024; Krieger et al., 2025). New skills are increasingly needed to manage these technologies, while at the same time there is a risk of deskilling in routine activities due to the automation of these tasks. There is no clear separation of roles, as specialist know-how remains in demand in everyday work. The elimination of routine tasks is usually offset by an increase in complex and flexible tasks. As Reinmann (2023) has already noted, targeted upskilling and reskilling measures must be implemented to create opportunities for the circumstances the balance . to . However, the balance of skills can only be addressed if the key competencies, such as critical thinking and problem-solving skills, that employees need to develop in this context are identified. If the challenge is not recognised, companies risk losing skills on the one hand, and on the other hand, work motivation may also decline. of employees suffer suffer.

Looking at the challenge of the low prevalence of generative AI, it quickly becomes apparent that it is one of the significant challenges in dealing with the technology. As analysed by Schaller et al. (2023), the percentage of EU companies using AI or planning to use it was around 13%. Compared to cloud computing, which is over 20% more widespread, it can be said that the use of AI is still in its infancy. In view of the challenge posed by the low prevalence of generative AI, the establishment of governance structures and the creation of a basis for training employees in the use of with the technology particularly . importance. Looking at the challenge of human-machine interaction with the three problem areas of bias, hallucinations and the use of unauthorised technologies, the following can be noted:

From the perspective of applying the human-machine interaction concept, it must be recognised that some studies indicate that the results of this generative AI are of very poor quality, as employees are regularly confronted with hallucinations or false statements from generative AI in practice, forcing them to constantly critically evaluate the AI-generated content.

to be reviewed (Hubel et al., 2024). And although generative AI can relieve us humans of a considerable amount of work, the ultimate responsibility for AI-generated responses still lies with the user. This is essentially one of the central aspects of human-machine interaction. In this context, Krieger et al. (2025) argue that awareness of critical thinking and judgement skills among employees must be strengthened. This will enable them to keep pace in a world of generative AI use. In addition, it has been found that a lack of training and incomplete governance processes in particular cause uncertainty among employees. This means that infrastructure and organisational culture are crucial to the success of a generative AI project . . . Concrete options for action on how to overcome these challenges are derived for the strategy areas of Further training, Governance and Human-in-the-loop . The studies by Hubel et al. (2024) and Krieger et al. (2025) provide the scientific background for deriving the option for action of providing training programmes in the field of generative AI. They conclude that employees must be trained accordingly in order to make optimal use of generative AI systems in practice. These programmes should cover a broad range of knowledge in the field of generative AI by providing both technically relevant information and training employees on ethical and legal challenges so that they can recognise the limitations of generative AI tools. These include the detection of bias, hallucinations and much more. Employees must also be empowered to correct these sources of error. Participatory governance processes with clear approval procedures and authorisations must be defined. To this end, it is necessary to ensure that the company's data protection guidelines are complied with by defining transparent data protection processes. In addition, employees should be given a say in the matter (Protschky et al., 2024). Human-in-the-loop interaction can be used for continuous error minimisation. In this case, improvements are made based on feedback from employees, data protection officers and other departments. This has a positive effect on trust in automated processes. The challenges in terms of efficiency, workload reduction and productivity will be briefly examined below. Studies by Majkovic et al. (2024) and Hubel et al. (2024) have shown that efficiency can be increased in various contexts through the use of generative AI. In return, there has been an increase in control and evaluation tasks, which can be the result of hallucinations and bias, as well as increased mental and cognitive stress in the knowledge work environment . . The increase in complex tasks also makes the requirements for flexibility at work and adaptability to changing conditions more demanding. It can therefore be deduced that employees perceive generative AI as making their work easier, but also as a flood of tasks, and that new mechanisms for stress management are needed on the part of companies .

In conclusion, it becomes clear that the challenges posed by generative AI require both a technical-organisational and an explicitly human perspective. Companies and research institutions alike must address the question of how to strike a balance between innovation and employee needs in order to exploit potential on the one hand and minimise risks on the other. The following paper discusses the theoretical foundations of generative AI.

1.3 Structure of the paper

The opportunities and risks of generative AI in everyday working life in Germany are considered from an employee perspective. A multitude of rules and insufficient training on the part of the company can lead to employees feeling overwhelmed when dealing with generative AI. This has been demonstrated, for example, by Hubel et al. (2024) and Neyer & Lehmann (2019). This creates enormous pressure to constantly correct faulty AI output, which weakens confidence in the technology. However, the use of generative AI, especially in administrative tasks, can lead to significant efficiency gains (Löll, 2024), which underscores the need for careful handling of this technology. The frequently described negative consequences of using generative AI are becoming clear: the cognitive strain caused by ambiguities and hallucinations, as well as bias issues, require constant monitoring by employees, often negating the actual benefits of the technology (Majkovic et al., 2024). The high validation effort and the lack of technological and organisational support lead to ongoing demotivation among employees. The use of generative AI is changing the roles of users to become control authorities, which is accompanied by new demands on employees.

Since generative AI has different areas of application, its consequences can vary greatly. For example, generative AI in customer communication often makes everyday work easier (through automation), while in software development, there is an enormous amount of validation work for the generated output (Al Haque et al., 2025).

While efficiency gains in the administrative area can be considered more clearly recognisable due to lower validation costs, these are often reduced again by multitasking and increased control requirements. This shows that increased workloads greatly increase the need for critical reflection, but that this is less pronounced than job involvement. job involvement of employees . . The literature analysis and case studies show that further training and clear governance are positive and beneficial resources. It has been empirically proven that further training for employees leads to greater professional competence and thus to greater satisfaction when working with generative AI (Aschemann et al., 2025). This means that, in addition to technical knowledge, training in how to use the technology is also of considerable importance.

This knowledge provides clear governance, such as the framework for generative AI governance described by Emett et al. (2023). This enables organisations to effectively and efficiently manage and control generative AI.

This can be divided into five areas, namely strategic orientation, data, operational activities, ethics and transparency. The participatory aspect in particular represents a fundamental basis in this framework for the application of generative AI in the German context.

Governance ensures transparency and clear guidelines for employees, enabling them to define their position in the work process when dealing with generative AI (Hubel et al., 2024). In order to prevent generative AI from becoming overwhelming, it is particularly important for management to work with employees rather than making decisions over their heads.

The problem areas of bias and hallucinations are associated with considerable challenges in human-machine interaction. Since no authorised usage processes are specified, private accounts that do not comply with the GDPR are increasingly being used for generative AI (Krieger et al., 2025). These uncertainties regarding data protection compliance are not only a psychological challenge, but also a practical one. To counteract such difficulties, participatory and transparent structures with regard to processes and methods are useful, as they create trust in the technology (Protschky et al., 2024). Clearly defined responsibility management is particularly crucial in order to optimise the use of the systems and to avoid incorrect decisions by the AI.

Social and psychological challenges such as feelings of alienation, mistrust and excessive demands should also be mentioned. These are usually triggered by a lack of employee involvement in generative AI decision-making processes (the introduction of rules and guidelines) and in the management of the technology (governance) (Huchler et al., 2020). Even if generative AI is developed for employees and is intended to simplify their work, it is essential to involve employees in the control process in order to prevent situations of excessive demands and loss of acceptance . Linking theoretical models with empirical research findings makes it possible to generate further hypotheses and solutions for practical application. The approaches of the Job Demands-Resources Model and Skill-Biased Technological Change show that the changed dynamics between employee demands and resources can be represented by generative AI in the context of everyday work (Butollo et al., 2024; Bryjolfsson et al., 2023). The research findings also show that personal and organisational influences are largely responsible for the acceptance of generative AI

(Protschky et al., 2024). Hybridisation is one of the most frequently cited organisational forms for dealing with generative AI in everyday working life (Hubel et al., 2024). In summary, it can be said that an integrated and systematic approach, consisting of technological, organisational and human influencing factors, is a crucial approach for considering generative AI from an employee perspective.

The combination of further training and a work process defined transparently by clear governance are key elements in dealing with the risk of overload, hallucinations and bias problems associated with generative AI.

2. Theoretical foundations of generative AI and large language models

The use and functioning of generative AI systems and large language models are a relevant part of this topic, as they form the technological basis of the applications used in companies. The following section discusses the possible areas of application, the theories and models used, and the necessary technical fundamentals.

2.1 Areas of application in companies

The many possibilities for applying generative AI tools in companies are particularly evident in the areas of customer communication, software development and data analysis. This reveals both opportunities and challenges. Some areas of application are examined in more detail below.

2.1.1 Customer communication

Generative AI tools in customer communication have the potential to offer personalised and automated communication. Customers can use them to submit their requests at any time, which significantly increases the company's availability in the evenings and on weekends. This is confirmed by the study by Hepp et al. (2022), which highlights that AI systems free employees from everyday routines, thereby increasing the company's service performance. Due to increased availability and automation, customers enjoy a significantly higher level of service quality, which puts considerable pressure on the company. This pressure, in turn, carries the risk that companies will rely on monitoring systems and adaptation processes . .

However, the use of generative AI tools can lead to an increased risk of incorrect or hallucinated responses from the AI, as their accuracy is not guaranteed and employees bear the responsibility. The study by Aldendorff and Löhe (2025) shows that bias in speech output can often lead to discriminatory or insensitive responses from generative AI tools. This causes enormous damage to the brand, which is why employees must be trained to deal with possible bias and to act ethically and socially responsibly when using of AI . . The use of personal data in customer communications also leads to considerable difficulties, as generative AI tools require a lot of sensitive data . The risk of data protection violations increases the more data is stored in generative AI tools, which is why operational governance must be adapted and employees' data protection skills improved (Protschky et al., 2024). In addition, the lack of clear rules for data security and its consequences can lead to significant problems, as in many cases data is lost due to violations of data protection guidelines or the company no longer appears trustworthy. Furthermore, companies often use private accounts or unofficial tools to process data more quickly. This in turn leads to a huge increase in data loss or security risks. However, continuous training and awareness campaigns are designed to enable employees to handle personal data responsibly and comply with data protection regulations .

As generative AI tools automate communication, this skill is less in demand, as this work is now increasingly being done by AI. The risk that employees will lose this knowledge in the long term due to automation and a lack of application of communication skills is also referred to as de-skilling. In addition, they may no longer be able to select suitable communication tools in critical situations . This leads to a deterioration in the skills and abilities of employees and a lack of experience. Knowledge and skills for interacting with AI systems, such as monitoring, adjustments and troubleshooting, are now increasingly needed (Küppers et al., 2023). If employees are not challenged or trained in this area, they may be left behind, as skills in everyday work with AI are becoming increasingly important due to new processes. This can lead to exclusion from the labour market. New skills can be learned if employees are trained in how to configure or further develop AI systems. This upskilling and reskilling enables employees to work with AI on a daily basis, which can lead to them learning valuable skills in their new job. The increasing need to monitor outputs is triggered by the inaccuracy of the AI system's responses. Generative AI tools have managed to replace many monotonous and repetitive tasks, thereby saving resources, but at the same time be consumed again by checking the outputs. Many tasks require a high degree of mental control and can also occur under time pressure during peak periods, which can lead to stressed employees (Hepp et al., 2022).

As a result, employees have to make many spontaneous decisions because the AI system makes mistakes that must be corrected immediately before they are passed on to customers. This requires a considerable judgement on the part of employees.

Another problem arises from the lack of integration of handover mechanisms when customers need to be transferred from generative AI tools to employees. Careless design of processes can place a burden on employees, as seamless and rapid handover is necessary for an optimal customer experience. In this case, agile methods are recommended. Depending on the type of enquiry, suitable processes must be determined in which, for example, the generative AI application takes over the enquiry or a human intervenes. Furthermore, the acceptance of generative AI within a company also plays a necessary role. Employees are more likely to reject AI systems if they fear they will have no control over the results (Hepp et al., 2022; Protschky et al., 2024). They also do not trust the accuracy of the output texts. To enable employees to identify better with the processes, it is therefore necessary to involve them in the introduction and selection of generative AI tools.

2.1.2 Software development

Software development is an important area of application for generative AI tools. It offers efficiency gains, but also presents challenges. Studies show that GitHub Copilot resulted in a massive reduction in processing time in some cases. Controlled experiments report significant speedups for narrowly defined tasks; in real-world projects, the effects vary greatly depending on the setting. (Peng et al., 2023). According to this, generative AI tools can help eliminate barriers to access to software development, thus providing inexperienced colleagues with more or less equal starting conditions for development processes. Other studies, however, show that the efficiency gains achieved through the use of generative AI depend heavily on the specific task, the expert knowledge of the developers and the specific integration of the tools into the workflow. The measured time savings vary considerably (Al Haque et al., 2025; Crowston & Bolici, 2025). This shows how important it is to take a differentiated view of the possible applications of generative AI tools in order to find an environment in which they can be fully exploited. Productivity gains through generative AI assistance systems can be observed primarily among junior developers or new employees. This is because acceptance of the technology is more pronounced in these groups, and complex development tasks can be tackled more easily with assistance (Crowston & Bolici, 2025).

This enables junior developers to complete tasks more quickly than in a conventional environment.

which are otherwise reserved for senior developers (Crowston & Bolici, 2025). This allows companies to utilise the labour of less experienced developers for more complex processes. Overall, companies thus benefit from a levelled knowledge base within the development team. According to a study by Falck et al. (2024), large companies (over 250 employees) are the most active users of generative AI technologies, while smaller companies increasingly show weaknesses in the infrastructure required to deploy these technologies.

Many companies report that employees use private access for generative AI applications – with associated risks for data protection, IT security and governance (Krieger et al., 2025).
This means that a company-wide policy for the introduction of generative AI tools is of considerable importance in order to comply with data protection and IT security requirements.
The integration of generative AI tools into software development can make programming tasks significantly easier, with less experienced developers often benefiting the most. At the same time, the cognitive effort is shifting towards reviewing and verifying the generated suggestions (Crowston & Bolici, 2025), which primarily benefits less experienced and younger developers. At the same time, the cognitive effort required of developers has shifted, as they now not only have to implement the AI-generated code, but also examine it for comprehensibility, functionality and possible sources of error. This, in turn, can lead to validation bottlenecks, as the capacity to read and review the output of AI is limited (Mozannar et al., 2025; Al Haque et al., 2025). Problem-solving skills, critical thinking and, above all, validation skills are becoming increasingly important. This is because AI-generated code often initiates incorrect troubleshooting, contains erroneous content or hallucinates (Al Haque et al., 2025). Despite the support provided by generative AI, human control is still unavoidable in most software development applications, which is reflected in the work requirements of developers .
Often, the perceived helpfulness of AI is much higher than its actual productivity. Developers state that the effort required for monitoring and post-processing negates the perceived benefits associated with the use of AI tools (Al Haque et al., 2025). Companies must therefore carefully balance productivity and efficiency gains with the actual number of hours worked by employees in order to avoid overload and impaired concentration (Crowston & Bolici, 2025). Although the quality of the generated code is acceptable, it requires more post-processing than code created through pair programming (Imai, cited in Al Haque et al., 2025). The review and debugging process is becoming increasingly important in software development. In safety-critical applications in particular, AI-generated code quality suffers from bias and hallucinations, as in many situations it is not yet able to incorporate domain knowledge and

implicit requirements into its development (Al Haque et al., 2025; Krieger et al., 2025).
Here, validation and critical thinking by employees are of central importance.

The targeted use of human-in-the-loop approaches in software development can be employed in companies to strike a balance between AI-generated output and human quality standards (Crowston & Bolici, 2025). This can improve efficiency and acceptance, as potential errors in the code can be reduced in professional development environments (Crowston & Bolici, 2025). The integration of generative AI tools into development processes allows for targeted upskilling and reskilling measures. This is because new and inexperienced employees can quickly learn and perform even complex programming tasks that are normally delegated to experienced colleagues (Crowston & Bolici, 2025). This means that the required level of expertise can be achieved more quickly. However, generative AI tools also reduce barriers to career change. Despite the potential of generative AI tools to automate certain programming processes, there is a risk. Routine tasks and tasks that require creativity (such as coding style, bug detection, finding solutions, etc.) could become increasingly irrelevant (Crowston & Bolici, 2025). These activities are thus practised less, resulting in the so-called de-skilling phenomenon. Targeted measures are required to maintain and promote the necessary human expertise of employees in companies, for example by adapting training programmes to promote the skills that are becoming less relevant due to the increased use of generative AI tools .

It has also become much easier for companies to hire career changers, people without a university degree and people without professional experience (Crowston & Bolici, 2025). The reduction in technical barriers to entry is changing the requirements for employees in the labour market. However, innovation and independence can be limited by AI-based support, as independence is based on a certain level of expertise that can be replaced by AI. However, the proactive involvement of employees in deciding whether to introduce generative AI tools, as well as in their implementation and the provision of additional task-specific training, can lead to increased acceptance and security of the systems in companies (Krieger et al., 2025; Crowston & Bolici, 2025).
The development of hybrid forms of work, in which generative AI tools can be used to relieve the burden on employees, but at the same time expertise and control are exercised by humans, represents a sensible approach (Krieger et al., 2025). This is also an efficient approach. In technology companies, for example, AI-generated code is used to

It has been met with enormous acceptance and few adaptation problems, as there is already a high degree of structure and compliance in this area (Crowston & Bolici, 2025). However, this is not the case throughout the entire DACH region. In German companies, the use of generative AI sometimes takes place outside of formalised processes; in some cases, unauthorised applications and private access are used. This points to gaps in governance and compliance that should be closed by clear guidelines and the provision of tested tools (Krieger et al., 2025). There are increasing indications of shadow AI/BYOAI in companies; employees sometimes use private access to AI services – with corresponding data protection and compliance risks (Krieger et al., 2025). There is therefore still a huge amount of catching up to do in the area of internal corporate governance in order to enable the sustainable use of generative AI tools and prevent IT security requirements and risks within the company. In summary, it can be said that the use of generative AI tools makes software programming significantly faster, less labour-intensive and requires less expertise . .
However, this also presents companies with new challenges.

2.1.3 Data analysis

Generative AI solutions can significantly accelerate information extraction compared to purely manual processes and relieve employees in data-intensive areas (e.g. taxation, financial analysis) from repetitive tasks (Beuther et al., 2024).

However, its applicability is limited due to technical dependencies, training requirements and implementation issues. This requires careful planning and adaptation of processes, especially in sensitive areas. At the same time, technical dependencies, training requirements and implementation hurdles remain relevant. Careful planning and process adaptation are therefore necessary in sensitive areas. The accuracy of AI-supported extractions is high in the use cases examined, but not error-free – human plausibility checks remain necessary (Beuther et al., 2024). It has been shown that although AI works very reliably, errors can still occur. The human need for control and plausibility checks of generated results are therefore a must. If AI were allowed to operate on its own, incorrect assumptions and conclusions would flow into decision-making processes and possibly with serious consequences .

The use of generative AI applications to extract information from (partially) unstructured data increases not only process runtimes but also decision-making accuracy through structured data processing. Predictions for new companies are made with an accuracy of 92% (Beuther et al., 2024). Whether a greater reliance on AI algorithms would negatively impact the strategic thinking of employees is questionable questioned. Although the positive characteristics are clearly recognisable, generative AI tools are rarely used in German companies. This is due to concerns about data security and control. The use of AI is often characterised by a cautious attitude on the part of employees, which can be attributed to scepticism, fear of loss of control, lack of transparency of algorithms or uncertainties in dealing with AI (Beuther et al., 2024; Al Naqbi et al., 2024). Increased controllability can boost employee confidence and reduce their reservations. This challenge highlights the need to design the introduction of AI not only technically, but also socioculturally . One of the most relevant factors for effectively integrating generative AI tools into data analysis is the quality and diversity of data sources. Poor quality, systematic bias, incompleteness or insufficient verification of training data can lead to incorrect assumptions and conclusions, which can influence a company's decision-making processes. This is confirmed by the study by Huchler et al. (2020). Inadequate data quality can further reinforce bias or encourage misinterpretation. Technical and organisational measures must be taken to ensure data quality and diversity and integrity . Raising employee awareness of the risks of data distortion is also a key aspect of initiatives.

Even data that contains errors must be read correctly from the data source in order to avoid serious misjudgements in the business environment that could result in financial losses. It is also important to keep an eye on the quality of the data used. There are a variety of ways to improve data quality and clean up data. At the technical level, data anonymisation and synthesis are proven strategies for reducing bias (Huchler et al., 2020). However, it has been shown that in most cases this is only possible with prior training on data quality risks and data quality guidelines (Huchler et al., 2020). The implementation of generative AI tools therefore usually also requires an upgrade of skills of employees.

AI is replacing tasks in the field of data analysis as automation advances. However, compared to traditional tasks where they manually cleaned and analysed data, employees will in future need analytical skills in areas such as interpretation and validation. The workload is therefore shifting (Al Naqbi et al., 2024). There is a loss of practical skills in the field of data analysis as these activities are no longer necessary. Employees must learn to deal with the uncertainty that AI brings. Companies should promote this upgrade of skills with upskilling or reskilling measures to counteract the counteract the described loss of skills in the workforce. Otherwise, classic, manually applied methods of data verification and cleansing may fall into oblivion .

Meta-knowledge about generated insights and critical thinking should be considered key skills in this context. Given that AI also leads to unintentional nonsense through automated data generation, it is becoming increasingly important to evaluate the quality and significance of the results .

Companies that invest in these skills are able to unleash the innovative potential of their employees and secure a competitive advantage (Al Naqbi et al., 2024). Training measures should be characterised by a high level of participation in programme design so that they are accepted and used by employees as meaningful. One of the biggest challenges in AI-supported data analysis is the risk of bias and hallucinations (Huchler et al., 2020). These distortions can be attributed to various causes, such as insufficient data quality, algorithmic limitations or incomplete incomplete context of AI models. They can lead to incorrect results and wrong decisions, which can have a massive impact on a company's overall decision-making. Monitoring results, for example in the context of human-in-the-loop approaches, is particularly important here. In this approach, the AI is supervised by a human being. This person serves as a control mechanism in the process to avoid bias and hallucinations. With the introduction of AI in data analysis processes, roles are shifting and employees are becoming gatekeepers of AI results. This phenomenon presents companies with the task of continually adapting their quality assurance processes and the judgemental competence of their employees . .

Regardless of the risks, controllability is a fundamental factor in enabling companies to effectively integrate generative AI tools into data analysis. According to studies, only about 15% of the companies surveyed have a systematic quality control process in place, while just as many are dissatisfied with the controllability of the system (Huchler et al., 2020). There is often a lack of feedback mechanisms for the AI tool used. A sustainable control concept for generative AI tools in data analysis includes the implementation of an escalation mechanism. In addition, it should be supported by a documented and traceable AI decision (Huchler et al., 2020) and by empowering employees to a critical approach to the AI support . This ensures that the controllability of the processes is guaranteed with the least possible loss of control

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A widely used method for the deployment of AI tools in data analysis, as offered by generative AI solutions, is not yet available, as studies show differences in the use of AI tools (Illgen et al., 2025). There is no uniform approach.

the use of generative AI applications at work. However, certain areas of application are emerging. The majority of respondents say they use generative AI tools regularly for brainstorming. Regular use of generative AI applications is also evident in text generation, and brainstorming is the most common area of application for AI tools in the workplace. The application is also frequently used for creating summaries, but not to the same extent as the aforementioned areas of application. Employees with a low frequency of use rate their usage competence as low, but this correlates little with the frequency of use. There are also significant differences in the assessment of the usefulness of AI tools. Those who use AI more frequently consider it more useful than those who use them less. The majority of employees use generative AI tools regularly, but there are also users with very low frequency of use.

Generative AI tools can offer significant added value in increasing the efficiency and reliability of data analysis in companies. However, there are challenges in terms of bias and hallucinations, as well as the newly acquired shift in tasks. An optimal balance between the capabilities of generative AI and the needs of companies should be addressed by combining needs-based integration of AI with targeted training measures for employees.

2.2 Relevant theories and models

Key theories and models support the understanding of human-machine interaction between employees and generative AI and explain the reasons for acceptance and the associated requirements. Challenges and design options for sustainable integration are then explained by considering selected approaches in order to highlight the opportunities and risks of human-machine interaction.

2.2.1 Job Demands-Resources Model

The Job Demands-Resources Model (JD-R) provides a solid basis for examining the impact of generative AI tools on the work situation of employees. The model describes the interplay between work-related demands (job demands) and resources (job resources). Depending on the characteristics of these two factors, the well-being and work performance of employees are influenced. This relationship is particularly interesting in the case of generative AI tools such as ChatGPT and Copilot, as they provide resources for reducing work overload as well as stress related to cognitive demands and work processes. For example, one study shows that employees' adaptability and perceived work overload can be improved if sufficient technological and personal resources are available (Hessari et al., 2024). At the same time, however, the use of AI also gives rise to new digital requirements, such as the critical review of AI outputs, the detection of hallucinations, etc. These in turn can lead to an increase in the cognitive load . The resource consists in the fact that generative artificial intelligence tools automate numerous processes and thus reducing the workload of employees . This can contribute to increased efficiency, greater flexibility and thus improved employee performance (André & Bauer, 2019; Hessari et al., 2024). As a result, the repetitive part of the work can be reduced and time freed up for employees to pursue more creative activities. In order to use these resources effectively, the provision of technological and personal resources is crucial. These include appropriate training opportunities that teach how to deal with bias, hallucinations and other sources of error in AI systems, as well as adaptive support systems that can assist the work process (Hessari et al., 2024; André & Bauer, 2019). Without these technological and personal resources, the advantages of generative AI can be exploited, but the work requirements remain unchanged or even increase.

The increased use of generative AI tools generates additional requirements in various areas of activity, which can make knowledge-intensive work particularly difficult and lead to cognitive overload. Employees must be able to check the quality of AI-generated outputs and recognise hallucinations and other sources of error. In these areas, humans take on a supervisory role, which can lead to multitasking and associated stress that is often not adequately assessed (Hessari et al., 2024; Butollo et al., 2024). This situation shows that generative AI tools can lead to a reduction in repetitive processes in the short term. In the medium term, however, this can also lead to the creation of additional tasks and thus to stress among employees if this is not compensated for in a way that is (e.g. B. through adapted structures). The JD-R model also shows that the balance between requirements and resources must be redesigned and reviewed repeatedly over time. The reason for this is that technological changes are dynamic and create new resources. Work pressure arises primarily when the resources offered by generative AI tools can be used without simultaneously generating adjustments and relief in terms of requirements. This intensifies control, validation and monitoring processes, which leads to additional stress for employees (Butollo et al., 2024; André & Bauer, 2019). For example, data-intensive and service-oriented

Workplaces are seeing significant time savings thanks to generative AI tools, but the new control and validation activities are placing additional demands on people, which in turn reduces efficiency. These findings show that it is essential to keep a close eye on the changes and thus the effects of generative AI on employees and organisations and to reassess them at regular intervals. With the increased use of generative AI tools, employees are increasingly being deployed as interface managers and are primarily taking on the role of error detectors (Butollo et al., 2024). It is important that employees are optimally prepared for their new tasks. The right training in how to use the technology is a top priority to prevent alienation. If the organisation does not provide training in this area, employees will feel uncomfortable. They have to trust the AI-generated suggestions and outputs, but there is still a certain residual risk (e.g. hallucinations, bias, etc.). Generative AI tools also limit the control function of humans. Employees are unable to understand why an AI application makes certain suggestions and must therefore rely on it to a greater or lesser extent. The lack of transparency and the lack of human involvement therefore lead to a loss of control and increased stress.

Alienation therefore becomes increasingly relevant when generative AI tools are used. For example, empirical studies show that alienation (loss of the feeling that one's own skills are useful) promotes a tendency towards expediency (i.e. choosing a short-term, simple solution). This, in turn, can imply unethical behaviour at work (e.g. embellishing working hours) (Hai et al., 2025). The control ratio also increases the risk of alienation in highly digitalised work situations. If digital requirements are increased and employees are thus controlled, the likelihood that they will unthinkingly accept AI inputs without questioning their correctness may increase. This leads to a loss of connection to one's own values and an increase in expediency.

The human-in-the-loop approach is a much-discussed topic when generative AI tools are used. The aim is not simply to force employees into a supervisory role, but to involve them more and in a reflective manner, thereby triggering an experience of control and autonomy (Butollo et al., 2024). Active employee involvement not only improves quality assurance and reduces work-related stress, but also makes employees feel more self-determined and motivated at work. Companies that pursue the human-in-the-loop approach and combine it with feedback mechanisms and further training, for example, generate greater job satisfaction but also less stress within the organisation (Hessari et al., 2024). This shows that implementing the human-in-the-loop approach is a must for generative AI tools. The JD-R model has thus provided a helpful basis for analysing the impact of generative AI on the work of people in companies and thus highlighting the need for company-wide governance and training policies due to generative AI.

2.2.2 Skill-biased technological change

The use of generative AI tools such as ChatGPT or Copilot is changing the skills required in the world of work. New skills such as digital and analytical skills are becoming increasingly important, while routine tasks are being automated by AI. Empirical findings show that professional experience is less influential on performance, as generative AI allows low-skilled employees and young talents to be classified in a similar performance segment to more experienced employees (Brynjolfsson et al., 2023; André & Bauer, 2019). With regard to complex problem-solving tasks, however, the question arises as to whether the use of AI will lower people's skill levels, as problem-solving processes become less frequent carried out carried out .

With the automation of many activities, employees will only participate in process chains to a limited extent and will develop less procedural knowledge and expertise. Employees will now take on control and monitoring activities and will be supported by the AI system in performing their tasks. The task of employees will be to check the output of generative AI tools for accuracy (André & Bauer, 2019; Huchler et al., 2020; Shneiderman, 2021). A key skill for employees will therefore be to recognise the error-prone nature of AI systems. Without the skills to detect and correct errors, there is a risk that employees will simply accept the AI results and continue working. In customer service and software jobs, less experienced employees have the opportunity to learn faster and perform better by using generative AI. This is in comparison to employees without AI support (Brynjolfsson et al., 2023). The use of generative AI to standardise workflows can have a positive impact on businesses, but a negative impact on human creativity. The risk of de-skilling in complex tasks always exists when generative AI solves the problem on its own and the employee is only responsible for checking and correcting . .
As a result, employees' own skills are rarely used, which can lead to them becoming alienated from their work (Huchler et al., 2020). Innovative ability can also suffer if AI means that employees no longer develop their own creative solutions.

The increasing use of generative AI systems is boosting demand for training programmes (upskilling and reskilling) in digital skills for detecting and correcting errors in generative AI outputs (André & Bauer, 2019; Shneiderman, 2021). The learning format of these training programmes should be tailored to employees' needs and linked to their everyday work. In sectors such as healthcare, where wrong decisions can have life-threatening consequences, employees must be trained in critical reflection , particularly (Headecke et al., 2023). Even after the use of generative AI systems, the responsibility for the accuracy of the output results lies in the hands of humans. Thus, critical reflection skills become a key qualification in the work with generative AI. The use of AI skills training can increase the level of error detection among employees. They take on the monitoring and correction tasks in the human-machine interaction process actively (André & Bauer, 2019).

Not only does the work become less demanding and tiring, it also becomes more monotonous. The type of work can be transformed from manual labour to monitoring work (André & Bauer, 2019; Shneiderman, 2021). However, the qualification requirements for employees have not only changed in terms of technical skills. Employees act as communicators in human-machine interaction. In this form, employees are the link between machines and other colleagues. This requires employees to have not only technical but also communication skills. The combination of these skills will enable successful human-machine interaction to be designed. As the controlling authority in AI-supported work, humans can assist in the execution of complex control and correction tasks . .

The non-participation of employees in the human-machine interaction process can lead to alienation and unethical behaviour (André & Bauer, 2019; Huchler et al., 2020). Non-participatory automation often leads to lower work motivation and alienation from work. It also inhibits people's ability to innovate. If used uncritically, generative AI can have a negative impact on the quality of work.

The use of generative AI tools has the potential to reinforce bias (Headecke et al., 2023; Shneiderman, 2021). If the training data is unbalanced, the system may unconsciously adopt and reinforce the patterns found in it.

In this regard, the work must be monitored and, if necessary, corrected by humans. To this end, AI must be structured transparently enough that the source of bias can be identified and addressed. To ensure that bias in generative AI systems can be detected and corrected, human skills in bias control must be further developed. Continuous collaboration between humans and machines is required, and thus appropriate human-in-the-loop models for controlling the output results.

The governance of generative AI systems must be changed to include regular quality assurance and feedback (Headecke et al., 2023). People must get involved and help drive the development of the systems. In addition to technical skills, social and labour law skills must also be developed.

2.2.3 Technology acceptance (TAM/UTAUT)

The acceptance of generative AI tools in German companies is primarily determined by their usefulness and user-friendliness, which are the central variables of the TAM and UTAUT TA models. Employees consider generative AI tools such as ChatGPT or Copilot to be useful if they offer clear added value, e.g. in terms of time savings or more complex tasks (Brynjolfsson et al., 2023). Ease of use, which is expressed, among other things, in simple and intuitive operation, is particularly essential for inexperienced employees, as a low barrier to entry leads to higher productivity gains (Crowston & Bolici, 2025).In customer service, for example, untrained employees were able to significantly increase the number of customer enquiries answered per unit of time with the help of generative AI compared to existing processes (Brynjolfsson et al., 2023). The usefulness in terms of the output generated varies depending on the workflow or task. While employees in junior positions welcome the benefits of generative AI tools, experienced staff may see negative effects such as a loss of competence. This can also affect their acceptance in question question (Crowston & Bolici, 2025). Trust is another factor influencing acceptance. Losses of trust in the use of generative AI, for example due to the risk of misunderstanding and the possibility of bias, hallucinations and unpredictability of generative AI tools, pose particular challenges that have a negative impact on the acceptance of generative AI in organisations . . (Protschky et al., 2024). The unpredictability of generative AI outputs and bias (i.e. algorithmic distortions) therefore represent significant concerns for employees (Protschky et al., 2024). These concerns can lead to employees either not using generative AI tools or limiting their use to the minimum necessary. Loss of trust can be caused, among other things, by a lack of transparency regarding the data basis and the functioning of the AI used (Caspers et al., 2025).

A study suggests that implementing human-in-the-loop approaches and feedback processes can help strengthen employees' trust in generative AI. This is achieved by allowing employees to influence or make critical decisions (Protschky et al., 2024). This means that a major challenge in the governance of generative AI tools is to establish trust-building and transparent mechanisms for the employees.

The application of generative AI also changes the distribution of tasks within the company and places demands on the adaptability of employees, which can influence acceptance. Employees with less experience can benefit significantly from the supportive function of generative AI. The assistance provided by generative AI tools enables them to tackle more complex tasks and increase their output (Brynjolfsson et al., 2023). This can lead to them accepting the use of generative AI, using it regularly and taking a positive view of new developments. Skilled and more experienced employees benefit less from the use of generative AI tools than untrained staff. This is because the advantage of the automation solution can manifest itself in the fact that they have to take on more responsibility for review and control tasks and may fear a loss of competence (Crowston & Bolici, 2025). This change in the distribution of work raises the issue of acceptance of the changed working conditions. Employees with different skills may find themselves in a situation where it is possible to respond to everyone's needs and at the same time enable all to , generative AI tools regularly to use.

Organisational and regulatory uncertainties also pose further challenges. Uncertainty about the GDPR compliance of generative AI and a lack of accountability or transparency in data flows can lead to increased concerns about the use of generative AI tools (Protschky et al., 2024). Some companies still do not have governance structures in place, leaving employees with concerns about data and no clear usage guidelines (Caspers et al., 2025). This can lead to the use of generative AI tools in a private setting without the employer's consent (e.g., ChatGPT). It can also lead to the use of the wrong AI tool (e.g. own or free account). This can increase risk and reduce acceptance (Caspers et al., 2025). Clear, participatory governance structures and employee co-determination in the design of AI guidelines are essential to reduce existing reservations (Protschky et al., 2024). Data protection concerns regarding the integrity of the technology used and potential cybersecurity risks are also key factors that should be taken into account when considering the acceptance of generative AI tools (Protschky et al., 2024; Caspers et al., 2025).

Closed-source or open-source solutions are powerful in most cases and capable of handling complex tasks, but they can raise concerns in terms of security risks (Caspers et al., 2025). Studies suggest that raising awareness of technical and ethical risks can help employees develop secure and confident usage skills (Protschky et al., 2024). This can be achieved through measures such as providing adaptive, practical training tailored to the target group of employees. Employees should be able to understand and minimise potential risks. Furthermore, it is necessary to embed processes and mechanisms for technical risk management in the organisation in order to involve employees in the monitoring, control, management and responsibility of generative AI (Protschky et al., 2024). Promoting technical skills and improving co-determination through the implementation of human-in-the-loop approaches and feedback loops can help to increase the acceptance of generative AI tools significantly . .

In summary, it can be said that the acceptance of generative AI tools in German companies poses a considerable challenge. In order to reap the long-term benefits of using generative AI and alleviate employee concerns, further training measures must be taken. Employees should be involved in the development and use of AI technology, and governance mechanisms should be established to create transparency.

2.2.4 Human-AI teaming and algorithmic management

Collaboration between humans and generative AI in a corporate context requires a fundamental restructuring of roles. Empirical studies show that generative AI tools such as GitHub Copilot are predominantly used by people with less experience, which allows for an improvement in the quality of work performance. However, using the tools also requires control and validation of the outputs, which in turn increases complexity (Al Haque et al., 2025; Huchler et al., 2020). Due to the hybrid division of labour, employees increasingly act as intermediaries between generative AI suggestions and execution.

Assessing plausibility and detecting errors are becoming core competencies for employees, as generative AI systems can also produce errors. There is therefore a risk that incorrect assessments will lead to wrong decisions being made, making digital judgement skills an essential skill (Al Haque et al., 2025). This role highlights the additional training requirements for employees in terms of their reflective and plausibility assessment skills.

Team acceptance and productivity are not a consequence of the performance of AI systems, but by the quality of the interaction between humans and machines . Studies show that successful human-AI teams are characterised by actively questioning AI suggestions and contributing to decision-making processes. Empowering employees for these new tasks in turn requires teaching digital judgement skills so that they can use the technology appropriately (Huchler et al., 2020). To use team structures effectively, responsive interfaces with embedded feedback loops are required. This allows employees to be effectively involved in monitoring AI systems. This facilitates control and increases the resilience of team interactions. A human-in-the-loop approach not only improves the quality of generative AI output, but also increases employees' sense of control and job satisfaction. (Huchler et al., 2020).

Algorithmic management is fundamentally changing the way work processes are controlled in companies. AI-supported technologies not only control and evaluate work performance, but are also increasingly taking on control functions. A distinction is made between algorithmic instructions and algorithmic evaluations. The former involves algorithmic pre-planning, control or allocation of tasks, whereas evaluation processes quantify and classify performance. For example, AI systems lead to automatic performance evaluation, algorithmic dismissals and monitoring (Huchler et al., 2020).

The control associated with algorithmic management is viewed positively, but the subjective impairments are not mitigated. Rather, the loss of freedom of action leads to employees becoming disconnected from their work (Huchler et et 2020).

In addition, algorithmic pre-planning reduces autonomy and at the same time increases control over work performance. The loss of control by employees means an increase in monitoring options, which makes them feel more controlled. Furthermore, when planning is done in advance by an algorithm, employees are restricted in their decision-making scope and forced to take certain courses of action. Since AI shows the possible courses of action, employees' scope for action is reduced (Krieger et al., 2025; Huchler et al., 2020).

Algorithmic control also changes the distribution of tasks. Tasks are automated, and employees are increasingly engaged in control tasks, such as

Evaluation of generative AI systems. In addition to IT skills, this also requires business management expertise, which cannot be assumed in many employees. The increasing number of tasks resulting from these responsibilities could cause psychological stress for the employees (Huchler et al., 2020).

Another problem lies in the de-skilling effects of algorithmic management. De-skilling means that automation causes employees to lose the ability to organise their work independently. This is problematic because generative AI can lead to de-skilling if no additional skills are learned and there is a lack of critical reflection on the generated results. Research shows that this can be a particular challenge in highly regulated or data-based industries. It is therefore essential that companies offer training opportunities that not only teach technical skills but also address work organisation (Huchler et al., 2020).

Another problem with human-AI teaming is the bias of the systems and algorithmic distortions. Algorithmic distortions, also known as bias, occur when social prejudices and "unclean" data sets are implemented in AI systems. Bias refers to systematic errors in a computer programme. These errors can be reduced, but this requires increased effort. In addition, many errors cannot be avoided at all, as the system is dependent on unclean data.
Here, too, employees are responsible for detecting distortions. However, since the errors are technical in nature, the inspector must have a certain level of IT competence. However, since not all occupational groups have this knowledge, it is necessary for employees to be qualified (Huchler et al., 2020; Klitzsch, 2025). The ability to correct the generated AI output is associated with control and monitoring obligations, which in turn can lead to an increase in cognitive demands. This is why skills in raising awareness of algorithmic risks are needed. For software developers and similar IT professions, identifying errors also requires more technical understanding than business management knowledge. An example: Generative AI delivers faulty code, and the developer inserts it unchanged. The developed algorithm does not work and throws error messages. Since the generative AI system cannot correct the errors in the generated code itself, the employee must implement the corrections themselves. As a result, the algorithm itself can become a source of errors that spread across the network. It is obvious that the faulty results have a significant impact on the team's work. Errors must be found and eliminated as quickly as possible to ensure that the network functions properly. In this case, a systemic control would be advisable, in which many algorithms are validated simultaneously, but this

Control processes are extremely costly (Klitzsch, 2025; Al Haque et al., 2025). De-skilling describes the risk of losing skills. Long-term use of generative AI systems may lead to a decline in critical thinking skills. Empirical studies show that, on average, young adults are less proficient in critical thinking than older adults. This may be due to the increasing use of algorithms and will become even more pronounced in the coming years (Klitzsch, 2025). Generative AI tools can be considered helpful, but they do not always lead to improvement.

Instead, bottlenecks arise in controlling and understanding AI outputs, leading to an increase in control work. Therefore, it is essential to train employees in critical thinking skills (Al Haque et al., 2025).

Furthermore, a culture of reskilling and meta-skills must be created for human-AI teams. Skills such as problem solving, judgement and reflection are needed to facilitate collaboration with AI systems and improve the quality of work (Klitzsch, 2025).
Governance structures are also necessary to involve employees in control and decision-making processes.

This will enable the technologies to be used optimally and reduce the effects of de-skilling (Klitzsch, 2025).

In conclusion, it should be noted that the acceptance and benefits of human-AI teams are significantly influenced by companies. Adaptive feedback structures and qualification and control systems can bring together the strengths of employees and technology (Huchler et al., 2020; Al Haque et al., 2025).

2.3 Legal and organisational framework conditions in Germany

The legal and organisational framework provides the basis for the responsible use of generative AI in German companies. The focus is on data protection, compliance, and co-determination and governance structures for secure and sustainable implementation. This section combines technical, legal, and organisational aspects to highlight opportunities and challenges in the German context.

2.3.1 Data protection and GDPR

Compliance with data protection and GDPR in the context of generative AI tools in German companies poses a considerable challenge. There is often a lack of clear and realistic regulations governing the use of personal data. This lack of regulation is particularly evident in the fact that many companies have not yet drawn up employee guidelines. These guidelines should be based on the principles of the GDPR and inform employees how they should implement data protection in their everyday work. This became clear, for example, when the Italian data protection authority temporarily banned ChatGPT (CEDPO AI Working Group, 2023; Leboukh et al., 2023). Due to the many uncertainties surrounding data protection and the GDPR, grey areas often arise in practice, posing risks for companies and employees.

The operation of generative AI systems often involves opaque algorithms based on huge data sets. This can result in data processing operations that are difficult for end users to understand. There is a risk that data leaks may occur unknowingly or that personal data may be used to train the AI. In such situations, unwanted data protection violations can quickly occur, which are difficult to detect and prevent (Dorn et al., 2023). This creates a high level of uncertainty among employees, which must be reduced with the help of clear guidelines for action within companies.
Furthermore, the cultural context of the company and its internal organisation have an influence on the implementation of measures to comply with data protection and the GDPR. Companies with a strong data protection culture consider the issue of data protection and the use of generative AI tools critically and regulate these strictly.
Companies with less awareness of data protection tend to give their employees more freedom to make decisions when using generative AI tools, which creates a higher compliance risk for them. Risk minimisation can be achieved, for example, with the help of data protection sponsors or a specific person responsible for AI governance. However, these forms of risk reduction are not widely used in business practice (Tobor, 2024).

In general, awareness training is necessary to promote employees' ability to recognise risks and respond appropriately. Studies show that without training programmes, the risk of unintentional data breaches by employees is significantly increased. This is partly due to the unconscious disclosure of information or a incorrect handling of AI-generated results (CEDPO AI Working Group, 2023). On the other hand, it is difficult for employees to assess whether, for example, an image generated by AI constitutes a data protection violation or whether AI should not be taken out of context and the product created should not be falsified in order to show it without further pointing out that it is a draft. In training workshops and scenarios that simulate real-life application situations, employees can learn to recognise risks at an early stage and actively counter them. Especially in data-sensitive areas such as customer service and human resources management, where there are risks of prompt leaking and manipulation of AI-generated content, should regular data protection training . Training and awareness measures also increase employees' personal responsibility in the area of data protection and in the context of using generative AI tools. They learn to recognise data protection violations and to speak up about them. If they can handle data minimisation when working with AI applications, security within the company is increased. At the same time, it removes their reluctance to work with and accept AI (Huchler et al., 2020).

In addition to training programmes, feedback and reporting mechanisms also help to raise awareness and strengthen risk awareness among employees. This can be achieved, for example, by setting up a company-owned internal portal with a wealth of information on data protection that is accessible to all employees. Alternatively, an internal reporting channel can also help to improve risk management in cases where employees do not have sufficient information. To this end, it is essential to actively integrate the risk assessment carried out by the employees themselves into the company's operations, as they are the most outstanding experts in the field of generative AI tools within companies and are therefore best placed to contribute their assessments to operational changes (Protschky et al., 2024). This reveals existing risks and enables employees to better comply with the new guidelines and rules of the data protection and of the GDPR in their everyday work.

Technical measures such as the privacy-by-design concept can make a significant contribution to compliance with data protection and the GDPR. In the privacy-by-design approach, which according to Article 25 GDPR aims to achieve data protection effects through technical design, certain processes are already defined in the design phase of the technical system. Automatic anonymisation and pseudonymisation procedures can be embedded in the AI system to render personal data unrecognisable before processing (CEDPO AI Working Group, 2023). This can increase both data security and employee confidence in the AI system. One way to approach the principles of privacy by design is to use the face blurring function of the video analysis software implemented in the cameras, which is activated before transmission to the company network (Huchler et al., 2020). Privacy by design is rarely taken into account in AI projects, which leads to various risks and a considerable

Additional expenditure incurred as a result of adapting existing concepts or supplementing new concepts.

To ensure that the AI system is designed in such a way that it complies with the principles of the GDPR in future, clear integration into the development structures of generative AI tools will be necessary. In addition, inclusion in the data protection concept will be required (CEDPO AI Working Group, 2023).

Employees are also essential for the successful integration of the new AI strategy. Therefore, effective governance is required to involve employees in the decision-making processes.

Governance models define responsibilities and create clear communication channels to coordinate interaction between data protection, the IT department and the respective specialist area. These mechanisms are still rarely used, which carries a considerable risk of uncontrolled use of generative AI tools in everyday work.

Furthermore, the involvement of employee representatives is essential to ensure broader acceptance and compliance with data protection guidelines (Protschky et al., 2024; Tobor, 2024).

Furthermore, compliance with data protection and the GDPR stands and falls with the technological expertise in companies.

A lack of technological understanding makes it difficult to comply with data protection requirements, as processes such as the classification of risks and sensitive data cannot take place without human and know-how resources. Companies must therefore continuously provide training and further education measures for their employees (Brüggemann et al., 2025). One option here is to set up interdisciplinary teams of experts with legal, technical and specialist skills. These interdisciplinary teams, which bring together IT, data protection officers, legal advisors and AI project teams, can be given an advisory role in the development of AI systems.

The work and the experts must be centralised and networked. This serves to reduce the fragmentation of responsibility and the risks associated with the use of AI in companies. . .

reduce (CEDPO AI Working Group,2023). In summary, the three levels – awareness programmes, technical precautions in the sense of privacy by design, and governance structures – eliminate many uncertainties and risks relating to data protection and the GDPR and enable employees to familiarise themselves with AI tools.

Companies must plan these three levels extensively and develop measures to ensure that AI-based tools can be successfully integrated into existing work processes.

2.3.2 Co-determination and works agreements

Employee co-determination and participation in companies is a crucial prerequisite for the successful implementation of generative AI tools. Research shows that the participatory involvement of employees has a positive effect on the acceptance and willingness to use generative AI tools (Protschky et al., 2024). If, on the other hand, generative AI tools are implemented without appropriate involvement, the chances of a decline in usage increase. If this resistance is not addressed at an early stage, it can hinder the productive use of ChatGPT & Co. and the associated generative AI, leading to operational problems and additional training costs. .

Another problem area is the often insufficiently detailed works agreements on the use of generative AI tools in companies. Most works agreements contain only vague wording.

The new requirements for the skills to be acquired or the risks associated with the use of generative AI are often not addressed in these works agreements. For example, only a significant proportion of all guidelines refer to skills in the area of data protection and data literacy (Tobor, 2024). Concrete instructions for the independent, data protection-compliant use of generative AI tools are therefore rarely specified.

A particular challenge with regard to co-determination and participation rights is the use of generative AI in personnel decisions in the area of recruitment. Current research shows that supporting selection processes with generative AI such as ChatGPT can lead to algorithmic discrimination, as a candidate's ethnicity, for example, can lead to exclusion or preferential treatment (Ali & DeAlmeida, 2024). This discrimination can create algorithmic risks for the company, which can lead to economic consequences . . The works agreement must therefore specify how algorithmic decisions are to be handled and, in particular, ensure equal opportunities.

The implementation of generative AI tools in companies and the associated work requirements lead to an increase in psychosocial stress for employees. The lack of or inadequate co-determination in connection with the implementation process of generative AI tools causes alienation among employees and a reduction in autonomy (Hai et al., 2025; Hubel et al., 2024). Effective participation rights, on the other hand, ensure quality of work, social justice and ethical standards. Co-determination can thus be seen as a functional element for mitigating the negative effects of the new technology, but also as an instrument for greater acceptance.

Against this backdrop, it is necessary to further develop existing corporate governance frameworks and establish transparent procedures for the use of generative AI tools with regard to both social and technical aspects. It is also necessary to create a process of co-determination for employees in order to enable the responsible design, use and control of generative AI tools (Hubel et al., 2024; Protschky et al., 2024).

3. Methodology

A structured examination of the applied research strategy forms the basis for investigating the opportunities and risks of generative AI in human-machine interaction. The focus here is on the approach used to answer the research question by means of literature review and evaluation.

3.1 Research design: Systematic literature review

The systematic literature analysis is carried out to answer the research question and shed light on the opportunities and risks of generative AI in human-machine interaction. The focus is on evaluating the current scientific literature, with a particular emphasis on the technological, socio-technological and psychological factors that shape the everyday working lives of employees in companies in Germany. Studies that also address bias, hallucinations and data protection issues in this context are examined. are also addressed (Seufert & Handschuh, 2024). A formalised literature review process enables a structured and comprehensible answer to be given to the research question. The literature review used follows a stringent search protocol that defines inclusion and exclusion criteria for the sources researched. These ensure the scientific soundness of the studies and their specific relevance to the German corporate context. Furthermore, an increasing number of empirical studies have been conducted that explore the perspective of employees on generative AI in everyday working life , including (CEDPO AI Working Group, 2023).

The interdisciplinary nature of the research design is reflected in the combination of approaches from business informatics, occupational psychology and technology assessment. This makes it possible to comprehensively evaluate the interactions between the functionalities of AI tools and organisational, personal and regulatory frameworks, and thus to derive areas of action for German companies (Seufert & Handschuh, 2024; Emett et al., 2023).

In addition to considering efficiency and stress factors, the focus is also on intervention and solution approaches such as further training and human-in-the-loop solutions. Governance aspects that are crucial for sustainable use (Seufert & Handschuh, 2024; Koch & Lodefalk, 2024; Emett et al., 2023) are also taken into account in the analysis.

The literature was searched using databases such as IEEE Xplore, SpringerLink and ScienceDirect, as well as websites with practical reports and white papers (CEDPO AI Working Group, 2023; Löll, 2024). By using multi-perspective search strategies such as "Generative AI AND workplace" and "AI data protection compliance" in German and English, both national and international research status is determined (CEDPO AI Working Group, 2023).

Current technical and regulatory changes in the subject area were taken into account so that current challenges facing German companies, for example due to new data protection guidelines or advances in generative AI infrastructure, could be examined (CEDPO AI Working Group, 2023; Nguyen et al., 2021). Case studies on specific implementation projects for generative AI applications (e.g. in university administration or in the area of IT-supported business processes) offer a high degree of practical relevance (Löll, 2024; Rigoll et al., 2024).

The study also seeks to identify gaps in research in the area of employee perspectives and the tension between AI application, organisation and skills development. For this reason, studies that do not address the perspective of employees or that answer purely technocratic questions were excluded (Rigoll et al., 2024; Nguyen et al., 2021; CEDPO AI Working Group, 2023).
Inclusion and exclusion criteria primarily relate to the research question, which focuses on the effects of generative AI tools on efficiency, data protection, bias, competence shifts and governance. Risks such as hallucinations or psychological stress are considered, as well as measures for a successful generative AI project, such as further training for the workforce or the development of AI governance (CEDPO AI Working Group, 2023; Tobor, 2024).
Emphasis is placed on the topicality and validity of the empirical results in order to derive recommendations for action for companies in Germany (Tobor, 2024; Emett et al., 2023).
The originality of the selected literature is ensured, as works dealing with topics such as psychological stress, ethical control issues or shifts in competence have been taken into account.
The thesis specifically formulated regarding the importance of governance and further training of the workforce is decisive in the selection of literature (Tobor, 2024; Emett et al., 2023).

The quality assessment of the sources is based on the replicability of the research design, the validity of the empirical results and the relevance for German companies. Only works with comprehensible methodology were included (Headecke et al., 2023). The high practical relevance with regard to efficiency, data protection and competencies enables the aforementioned effects to be evaluated on an evidence-based basis.

Empirical results on explicit competence models or experience reports were used to derive further training requirements (Tobor, 2024; Rigoll et al., 2024). The depth of the assessment was determined using assurance levels. This allows the validity and soundness of risks such as bias and hallucinations to be checked at different levels (e.g. assessment of the entire system, individual sub-areas, etc.) (Headecke et al., 2023).

The timeliness of regulatory changes is assessed in order to refer to compliance and co-determination in generative AI projects in accordance with the applicable legal situation. This increases the practicality and soundness of recommendations for action for everyday business life in Germany (Tobor, 2024; Rigoll et al., 2024). Research on competence changes and organisational learning was also used to assess upskilling/reskilling potential and the effectiveness of further training (Tobor, 2024; Rigoll et al., 2024).

Through targeted data extraction, the main causes of key problem areas in topics such as bias, hallucinations, competency profile requirements, multitasking, technology acceptance and the influence of personality on stress could be identified. Empirical findings on multitasking requirements and measures for protecting privacy according to the principle of privacy by design offer a wide range of solutions for addressing the identified problem areas (Beuther et al., 2024; Huchler et al., 2020).

3.2 Databases and search strategy

The targeted search for scientific databases and practice-oriented literature was an important criterion for selecting suitable sources in order to ensure a current and relevant selection of literature in the field of human-machine interaction in relation to generative AI. Databases such as IEEE Xplore, SpringerLink and Elsevier ScienceDirect were searched for empirical studies on the use of ChatGPT, Copilot and similar generative AI tools in German companies from the perspective of employees (Rigoll et al., 2024; Löll, 2024). White papers, such as those from the Research Centre for Information Technology (FZI), were also searched. These provide insights into best practice projects from companies with regard to topics such as governance, data protection procedures and efficiency gains (Rigoll et al., 2024). The inclusion of practical sources in the search is relevant because the topic of this thesis is tailored to the field of application of generative AI in administrative activities tailored . (Löll, 2024).

The search strategy was designed to be multi-perspective in order to ensure that relevant lines of research could be included and different dimensions (technological and socio-cultural) identified. Key terms such as "Generative AI AND workplace",
"AI data protection compliance" and "ChatGPT hallucinations" were entered in both German and English to capture a wide range of articles and ensure different regional orientations of work with generative AI (CEDPO AI Working Group, 2023; Löll, 2024). The multi-perspective approach enables a comprehensive coverage of key topics such as efficiency gains, bias, skill shifts and co-determination. Furthermore, the multi-perspective approach makes it possible to include literature from different disciplines, such as business informatics, psychology, and regulatory research, in order to meet both qualitative and quantitative requirements of the work and to identify and address existing research gaps regarding the explicit consideration of the employee perspective in the German context. address existing research gaps regarding the explicit consideration of the employee perspective in the German context.
The selection of technological and regulatory developments as starting points in the literature review should enable a future-oriented search strategy in which challenges and opportunities in the operational use of generative AI can be identified at an early stage. Developments such as future technologies (e.g. 6G) and infrastructures (e.g. energy efficiency of AI models) were analysed (Nguyen et al., 2021). The technological focus was complemented by research into regulatory developments such as new laws or regulations, for example the AI Act or Privacy by Design (CEDPO AI Working Group, 2023).
In order to provide insights into the practical application of this research project in addition to its theoretical interpretation, case studies (e.g. internal university project
"Generative AI tools for administrative tasks" to gain insights into the acceptance and efficiency of generative AI in the work context (Löll, 2024)) and case studies from practice, for example via the FZI (Rigoll et al., 2024), were used. Such studies provide empirical findings on technical requirements, implementation costs and regulatory requirements for the use of GPAI models. Based on the various areas of application of general-purpose AI models (GPAI models), these case studies enable the extraction of quantitative data. This data can relate to efficiency gains, for example. It is also possible to extract qualitative data, for example on the increase in data protection risks or changes in

skills. In this step, recommendations for action can be derived directly for a specific business context

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Based on the identified literature, the recognised challenges and opportunities, the regulatory and technological development trends, and the case studies from companies, the search strategy is suitable for identifying research gaps in the areas of bias, cognitive overload and governance, as well as the employee perspective, by combining interdisciplinary source selection, consideration of regulatory and technological aspects, and the inclusion of practice-oriented case studies, the search strategy is suitable for identifying research gaps in the areas of bias, cognitive overload and governance, as well as the employee perspective, and for establishing a central hypothesis (Rigoll et al., 2024; Nguyen et al., 2021; CEDPO AI Working Group, 2023; Löll, 2024).

To ensure transparency in the selection process, the screening procedure was documented in writing in accordance with PRISMA. Google Scholar, IEEE Xplore, SpringerLink and ScienceDirect (DE/EN; 2019–2025) were used to initially identify n = 870 hits and n = 50 additional sources obtained through snowball sampling. After duplicate removal, **n = 400** data sets remained. In the title and abstract screening, approximately 300 studies were excluded due to a lack of employee focus and incorrect context. Of the remaining studies, 86 were included in the full-text review and 76 were excluded. **n = 10** sources were included in the qualitative synthesis (final N of the study).

Table 1: PRISMA flow chart (own representation)

Database hits	n = 870
Snowball sampling	n = 50
Total before duplicate removal	n = 920
Duplicates removed	n = 520
Entries without duplication	n = 400
Screening excluded	n = 300
Full texts checked	n = 86
Full text suitability excluded	n = 71
Finally included	n = 10

3.3 Inclusion and exclusion criteria

The inclusion and exclusion criteria are intended to ensure that the analyses of human-machine interaction in the context of generative AI are relevant. To this end, it is essential to focus on the perspective of employees, the regulatory framework and the influences of technology. The inclusion of relevant sources and studies was deliberately realistic and

This means that studies dealing with the application of generative AI in German companies and empirically recording its effects were included. To this end, sources were considered that highlight opportunities and risks at the employee level and that were examined through the application of generative AI tools. Furthermore, publications dealing with topics such as efficiency, bias, data protection, governance or shifts in competence in relation to employees were also included. Sources that had no reference to the everyday working life of employees were excluded (CEDPO-AI Working Group, 2023; Tobor, 2024).

Another criterion was that the publications had to originate either from Germany or from a regulatory environment with a comparable context (such as Europe). Since the results of a foreign study cannot be transferred without restriction to the German context, partly due to the legal environment but also due to the work culture, the requirement was that the focus should be on the German or European environment. Furthermore, only sources whose content is verifiable and based on facts were selected. This served to exclude purely speculative and hypothetical results. By including governance, data protection and bias, all problem areas are to be examined holistically. Studies dealing with the implementation or development of governance frameworks or risk management were therefore included. This is crucial for compliance and the acceptance of AI applications by employees (Emett et al., 2023). In addition, sources were also consulted that deal with regulatory aspects and/or data protection aspects , such as , e.g. , GDPR and , privacy-by-design principles. These are considered in the application context of generative AI and represent an indispensable link to the risks and associated responsibility issues for employees. An explicit criterion for selection was that publications also clearly identify risk areas such as hallucination, bias, multitasking or cognitive overload and highlight their impact on the organisational possibilities of AI applications in the company and the ability of employees to act. To address these challenges, studies were also included that empirically address possible solutions in the form of human-in-the-loop approaches, targeted employee training and participatory governance structures in order to present possible recommendations in the results section of the paper (Tobor, 2024; Emett et al., 2023).
Another feature was the selection criterion of topicality, which was to be reflected above all in the application of research results. Therefore, only works that are empirically proven and present results collected using comprehensible methods were selected. These included studies that deal with the topic of generative AI in German companies and focus on various effects such as efficiency, data protection, shifts in competence

or governance. It was therefore decided not to include guidelines and publications that do not contain any empirical findings and results. This seems important given the enormous dynamics and development of generative AI on the market and the significant and current challenges from companies in the work context . In order to demonstrate relevance and ensure that the study results can be transferred to the German economic area, a critical assessment was carried out based on the current framework conditions, such as data protection laws and the German organisational context. Case studies and practical examples are of particular interest in this context, as they provide insights into practical requirements and reflect the applicability of AI tools (CEDPO AI Working Group, 2023; Tobor, 2024).

In addition, studies that report on a purely technological or theoretical approach were filtered out. The reason for this is that such studies do not allow conclusions to be drawn about employees and governance in the context of generative AI, nor do they reflect the risk at the individual level. Thus, those publications were selected that examine the impact at the organisational and employee levels. As a result, the findings often focus on technical possibilities and innovations as well as mathematical modelling, without making any statements about ethical or organisational consequences. In the study selection process, preference was therefore given to literature sources that empirically demonstrate both risk and solution scenarios (e.g. dealing with bias) and qualification measures such as data protection training for employees. However, theoretical models were taken into account if they could be supplemented by empirical findings and thus contribute to the evaluation of human-machine interaction (Osler, 2023; Tobor, 2024).

The practical relevance and effort to keep the research up to date were particularly evident in studies that addressed factors influencing employees, such as stressors, psychological strain, and issues of competence and control. In addition, new risks of generative AI, such as hallucinations or the effects of multitasking, which have not been studied or have been studied only to a limited extent, were also included. The selection of these studies provides a comprehensive view of human-machine interaction at work. In addition, the preliminary hypotheses of the study, which emphasise in particular the importance of governance and qualification through further training opportunities, are incorporated into the analysis. Based on the literature, it was discussed whether the research results can confirm these hypotheses. In particular, the focus was on avoiding wrong decisions and promoting acceptance through specific continuing education measures. Sources dealing with organisational learning and social control were also included in the selection in order to cover the perspective of employees with regard to new topics on the one hand and on the other hand, to refine the preliminary hypotheses based on the theoretical part (Tobor, 2024; Emett et al., 2023). The selection criteria mentioned above are primarily aimed at working with the research results of generative AI in a fact-oriented manner and not engaging in a purely fictional discussion in the literature . Since many sources deal primarily with the risks of the technology, care was taken to ensure that the selected publications represent the current state of knowledge, reveal new risks and thus contribute to improving human-machine interaction.

3.4 Quality assessment of the studies

The critical assessment of the methodological transparency and repeatability of the studies formed a fundamental basis for ensuring the comparability and transferability of the statements on human-machine interaction of generative AI tools. Methodological disclosure requires the presentation of the analysis methods so that effects such as bias, hallucinations or efficiency gains in operational use and their characteristics can be demonstrated (Headecke et al., 2023). This disclosure enables critical replicability and reveals methodological weaknesses in data collection or
analysis are revealed. In the repeatability review, the guarantees with which results from third-party studies can be reproduced were assessed. These primarily consist of standardised assessment scales and reproducible test protocols to minimise distortions that can occur due to the varying quality of AI models (Headecke et al., 2023). The assessment of weaknesses or limitations in the respective methodological approaches was then reviewed to determine the extent to which the studies produced transferable results for different companies, industries or occupational groups.

The assessment of the practical relevance and empirical nature of the studies required application to real work situations in German companies. Therefore, preference was given to studies that included concrete practical examples or quantitative field studies relating to German companies. With reference to the AIComp competence model, this fact allows for the assessment of realistic competence requirements that arise for employees through the use of generative AI (Tobor, 2024). Studies that take the employee perspective and thus assess changes in work requirements, necessary competencies or other psychosocial stresses (Tobor, 2024) were evaluated in a practical manner. The comparability of statements about human-machine interaction in German companies was further examined in terms of the diversity of the industries and company sizes considered. The depth of evaluation and assurance level of a study are crucial for risk and solution analyses in areas such as distortion or hallucinations. Multi-stage testing procedures

According to Headecke et al. (2023), these offer greater certainty as to how the low reliability of generative AI tools should be assessed in the work of employees. These test procedures include, for example, checks of AI results in real-world tests or in a simulation test scenario. Such procedures enable an in-depth theoretical and practical analysis of the challenges of generative AI. The depth of the assessment allows superficial statements to be distinguished from more profound ones with regard to the development of sustainable governance. Studies that do not differentiate between risks or possibilities for controlling the respective effects are deficient and can only derive statements at a very general level for German companies .

The regulatory context influences the validity of the study. Therefore, only those studies that consider the regulatory context in Germany and the EU as an evaluation benchmark for human-machine interaction were included. Knowledge of the respective legal compliance requirements allows practical recommendations for action to be derived (Tobor, 2024; Rigoll et al., 2024). Conclusions about compliance with data protection and co-determination were considered on the basis of relevant laws such as the GDPR, the AI Act or regulations within the company itself. Analyses that cannot provide answers to questions about the regulatory context or its influence on daily work may lose relevance. In addition, critical reflection is needed on how employees and companies actually respond to laws and standards and where information gaps or unresolved obstacles still exist. To ensure that conclusions remain practical in the coming years, emphasis was placed on timeliness, as this aspect in particular influences the validity of the studies . . The relevance for skill shifts and organisational learning was critically assessed in the studies using empirical skill models. Studies with sound data on changes in skills form a suitable basis for upskilling/reskilling. These show that continuing education, adaptive learning platforms and the participatory development of skills are becoming increasingly important (Tobor, 2024; Rigoll et al., 2024). Studies that present one-sided statements about de-skilling without offering solutions for sustainable competence development do not contribute to the added value of addressing the topic. The results of the study showed the following. The analysis and validation of meta-skills (e.g. critical thinking, reviewing results, problem solving) is an essential basis for highlighting skill shifts and integrating employees into a skills-based work process . .
Differentiations between opportunity and risk analyses were another quality criterion. The studies were examined to determine whether both areas were evaluated using figures, facts and critical conclusions, or whether they focused one-sidedly on opportunities such as efficiency gains (Demary &

Mertens, 2023; Tobor, 2024). Study results that critically addressed both areas were more meaningful than those that did not take into account challenges such as overload, ethical control or lack of information. The systematic treatment of multitasking, algorithmic control and the human-in-the-loop approach enabled the derivation of practical recommendations. Studies that analysed the above-mentioned aspects unsystematically or with a limited factual basis did not lead to any transferable conclusions regarding the risks of human-machine interaction in companies. Furthermore, the extent to which the weaknesses and limitations of the research results were reflected upon was critically examined.

3.5 Data extraction and synthesis

The systematic data extraction of problem areas relating to bias, hallucinations and employee competencies illustrates how discrimination and incorrect AI outputs can arise in everyday life. One of the most crucial challenges here is that discrimination can be triggered by pre-existing biases in the training data and algorithms, often resulting in unrecognised stereotypical and discriminatory outputs (Huchler et al., 2020; Beuther et al., 2024).

At the same time, it is shown that the detection of distortions or hallucinations is not possible without knowledge of the relevant test metrics, and that employees' skills must therefore be upgraded. However, a significant proportion of generative AI always provides correct answers – this has been empirically proven in the field of taxation, for example, where only just under 54% of tax payments were provided with correct information. This figure illustrates that employees act as a controlling authority in the interaction processes between humans and machines . . (Beuther et al., 2024).

Data collection for the study of the effects of data protection and compliance on human-machine interaction shows how technical measures such as privacy by design can reduce risks. This is demonstrated by the solution to the data protection problem of facial recognition AI, in which images are anonymised directly upon capture (Huchler et al., 2020). However, the actual effectiveness of such technical measures cannot be guaranteed if staff have not been adequately trained in their use. Our own work suggests that training should not only impart mere explicit knowledge, but also identify and eliminate potential for misuse and sources of error (Emett et al., 2023). This highlights the need for governance frameworks with control mechanisms, which a high level of security and trustworthiness beyond company boundaries (Protschky et al., 2024).

Looking at the effects on efficiency gains compared to cognitive load, it becomes clear that the use of tools with generative AI creates potential for efficiency gains. Reducing process runtimes can save up to 50% of the time originally required (Beuther et al., 2024). This goes hand in hand with additional control and validation by employees, which increases the cognitive risk in error-prone processes. However, studies also show that multitasking and other control measures to reduce risks tend to increase mental workload (Huchler et al., 2020). In this area, human-in-the-loop approaches and adaptive interface design can be used as control instruments to reduce cognitive load and perform active quality assurance with the technology (Beuther et al., 2024).
The survey on skill shifts and upskilling and reskilling measures illustrates that the use of generative AI in regulated and knowledge-based areas of the company is bringing about a shift in skills. This is because automation will increasingly reduce routine tasks, which will also reduce the need for employees to perform these activities. Competencies in analysis, reflection and control of generative AI expenditure are becoming increasingly relevant. However, shifts in competencies carry the risk that competencies will also become de-skilled (Beuther et al., 2024; Hofemann, 2006). This carries the risk that, without targeted further training, staff will need measures to keep their know-how up to date. To this end, a systematic skills development programme must be created that addresses a broad spectrum of skills through specialised training. Without such a programme, there is a risk that the use of generative AI will relegate employees to the role of the controller (Beuther et al., 2024). When evaluating governance theories and hypotheses about the effectiveness of tiered models and participatory control, the following observations can be made. Existing governance approaches do not focus on employees, but rather on other stakeholders, the IT system or the technological environment.
Therefore, when evaluating the studies we have collected, participatory control mechanisms and continuous learning are highlighted as fundamental factors (Emett et al., 2023). This leads to the assumption that governance only works if it encompasses technological, organisational and personal measures. The ability to articulate one's own needs and the flexibility to adapt quickly to changing requirements are identified as essential components of resilient companies (Emett et al., 2023). The existing models can therefore be further developed by incorporating the

network of technologies, people and organisations even deeper considered .

It has thus been shown that the systematic extraction and synthesis of data from studies provides an excellent basis for systematically identifying and deducing the risks and opportunities of generative AI in the workplace. The following sections differentiate between the problem areas of human-machine interaction in the individual chapters.

4. Results of the literature review – problem areas of human-machine interaction

The literature search and screening are documented in Chapter 3.2 (PRISMA-Mini). After duplicate removal, title/abstract screening and full-text review, a total of **n = 10** sources were included in the qualitative synthesis. The quality of evidence was classified in accordance with Chapter 3.4 (peer review status, contextual fit, methodological rigour, timeliness). The evaluation consistently focuses on the employee perspective in German and European corporate contexts.

The aim of this chapter is to identify the central problem areas of human-machine interaction in the use of generative AI in everyday working life and thus lay the foundation for practical action strategies. Four recurring problem areas can be identified in the included literature:

- **Bias/hallucinations:** systematic distortions or invented content in AI outputs that may appear plausible. For employees, this means that they have a duty to recognise and professionally validate results before they are used further.
- **Data protection/compliance:** risks arising from sensitive information in prompts and requirements for traceability, rights clarification and auditability at user level (e.g. "What is allowed in which tool?").
- **Cognitive load & efficiency:** Accelerating repetitive tasks comes at the cost of additional effort for context preparation, prompt design, result verification and tool switching; the net effect depends on the task, the maturity of the users and the clarity of the process.
- **Skill shifts: Upskilling/reskilling** (prompting, data/AI skills, source criticism) versus potential **deskilling** in highly automated routines; roles are changing from creator to curator/reviewer of AI outputs.

The following subchapters explore these four problem areas in more depth from the perspective of employees. They present the findings of the included studies and derive concrete consequences for the safe and effective use of generative AI in a corporate context.

Table 2: Results of the analysis (own representation)

Majkovic et al. (2024, ZHAW)	Efficiency and flexibility increase, but results must be consistently validated by experts due to hallucinations/bias .
Krieger et al. (2025, VDI/VDE)	Noticeable productivity gains in engineering roles, but at the same time risks from shadow AI and de-skilling → governance & process integration necessary.
Hubel et al. (2024, BMAS)	Activities will by 2030 be hybridised; Training requirements and burdens decrease when processes and further training are well designed.
Protschky/Schüll/Urbach (2024)	Risk management is successful with HITL, traceability and clear responsibilities up to the user level (auditability, rights, processes).
Löll (2024)	Administrative routines are accelerated when users prompting and check steps ; pure automation without review increases the risk of errors.
Morlock et al. (2025)	In product development, the role of creator to curator/reviewer; Use of co-pilots reduces routine tasks
Kaltenbrunner/Henne (2024)	Efficiency gains can be accompanied by a loss of autonomy and "alert fatigue"; transparent task design reduces these trade-offs.
Crowston/Bolici (2025)	AI generates upskilling and de-skilling in parallel; teams benefit when continuous learning and knowledge retention are institutionalised.
Peng et al. (2023)	Developers solve subtasks significantly faster, provided that code review/testing remains a mandatory step and overconfidence is avoided.
Beuther et al. (2024, DFKI/WTS)	In the field of taxation, added value can only be created with strict data /legal control; clear prompt and data guidelines prevent compliance leaks.

4.1 Overview of the research situation

There are numerous findings from research into the use of generative AI tools such as ChatGPT and Copilot in German companies. The majority of the various studies have found that 38 percent of respondents regularly use generative AI tools. The distribution of AI use among different age groups is interesting, with younger people (Generation Z) using it much more often than older generations (Majkovic et al., 2024). This points to a new technological stratification in companies. This stratification widens the gap between younger and older people in terms of AI and , thereby , , , inequality , , use , within , , companies .

Another finding from the studies is the use of free, publicly available AI tools, which are used privately and without consultation with the companies. This raises various questions regarding IT security and data protection (Krieger et al., 2025). In addition, it has been shown that a lack of infrastructural and organisational support from companies can encourage independent use, exposing companies to the risk of making wrong decisions. Furthermore, the question arises as to whether this type of use is sustainable in the long term with regard to Regulation (Protschky et al., 2024). The findings of the studies show that the advantage of generative AI tools lies in the automation of routine administrative tasks. These can be automated by up to 80 per cent by medical assistants, for example (Kaltenbrunner & Henne, 2024). Another finding is that the potential for automation brings with it an immense increase in work speed, but is also associated with additional validation tasks. These require additional time and cognitive effort, which relativises the increased performance and brings with it new challenges. Although automation leads to a significant increase in output, as studies have shown, the subsequent qualitative follow-up checks require time and effort (Kaltenbrunner & Henne, 2024). Overall, the workload increases in terms of additional cognitive work. Furthermore, there is a risk of bias or hallucination in AI applications. Study results indicate that the majority of AI users regularly check their results and rarely use the results generated by generative AI tools unfiltered (Majkovic et al., 2024). This shows that users are aware of the susceptibility to errors. It also points to the strain and overload on employees in terms of the additional work involved in troubleshooting or detecting bias and hallucination. However, the study hardly addresses the question of how skilled users are at detecting errors. Against the backdrop of the literature, the potential for automation is often relativised by the subsequent control tasks, which is why new challenges arise in the design of work (Sahoo et al., 2024).

In addition to overload, the risk to data protection is a key issue in the use of AI. Data protection must be taken into account during development. Therefore, approaches such as privacy by design and privacy by default should be a fundamental part of technology and application development (Villegas-Ch & García-Ortiz, 2023). Although studies show that it is technically feasible to ensure data protection in applications, they also show that the organisational requirements on the part of companies are usually insufficient at present.

Only a small minority of companies have already established their own guidelines that contribute to building data protection competence and awareness among employees (Tobor, 2024). When companies use generative AI tools, there is therefore a conflict between technical feasibility, a lack of clarity regarding regulation, and the usage needs of employees. To promote acceptance, companies are now called upon to develop appropriate concepts and solutions for data protection. Although there is already a wealth of research in the field of human-machine interaction, there is still a lack of relevant work on the topic of mental health and well-being. Studies mainly focus on how technologies work and neglect psychosocial and emotional factors (Robelski & Wischniewski, 2018). In addition, there are still considerable research gaps with regard to other issues relating to the use of AI in the workplace. The multiple effects of AI use, which lead to simultaneous relief, additional cognitive demands and increased quantity, have still not been sufficiently researched. Future research could, on the one hand, explicitly analyse individual stresses and relate them to other factors, including organisational ones. In addition, solution strategies can be found to counteract stress caused by generative AI tools in the workplace, thereby strengthening occupational safety and the mental health of employees .

The findings summarised above provide information about the current use of generative AI tools in everyday working life. Nevertheless, there is still a challenge to explore the issues identified in the literature and their consequences in order to examine them in greater depth in the context of everyday working life.

4.2 Bias and hallucinations: recognition, risks and solutions by employees

The ability of employees to identify and assess bias in generative AI systems is a crucial prerequisite for the successful application of these systems.

Technology in a professional context. Bias usually arises from insufficiently trained or insufficiently diversified training data, which leads to stereotypes and social patterns being reproduced in AI-generated outputs. Advanced metrics such as WEAT, SEAT, MAC and benchmark datasets such as Stereoset, Crows-Pairs and BBQ (Sahoo et al., 2024) help to identify bias. These are metrics that quantify bias in text data, but specialised knowledge is often required for their implementation. Participatory workshops, on the other hand, activate employees in identifying bias in generative AI, thereby strengthening their ability to recognise for stereotypes and discriminatory outputs. In addition to the risk of bias in generative AI outputs, the development and use of generative AI also carries the risk of hallucinations, in which AI systems generate false or fabricated outputs. The danger for companies is that the results generated by AI could be accepted uncritically by employees, which could lead to an increase in the risk of incorrect decisions (Siebert, 2024). Research shows that comprehensive models such as GPT-3 often make contradictory statements, which is why AI outputs must be continuously validated by humans (Sahoo et al., 2024). These additional work processes are time-consuming and must be factored into employees' daily work schedules. It is therefore essential to implement governance systems that clearly define responsibilities for quality control of AI outputs and derive measures to minimise risks. It is also important to integrate training courses that help employees learn how to perform checks using checklists, plausibility checks and feedback loops.

Bias and hallucinations in generative AI systems can be reduced through soft and hard debiasing in word embeddings, as well as retrieval-based correction measures that help to reduce the hallucination rate and bias (Towhidul Islam Tonmoy et al., 2024). These control mechanisms include mFACT, EVER and DRESS. DRESS has improved the trustworthiness and honesty of AI-generated texts, while EVER relies on data retrieval for correction, thereby achieving a significant advantage.

The development of mechanisms that reduce risks requires employees to be competent in using the control instruments. Employees must be able to recognise uncertainties and perceptions and assess the use of external validation sources on a case-by-case basis. This process is supported by the creation of a control guide in the departments and teams, which also promotes communication and coordination. In addition, it is crucial to constantly update training on correction mechanisms and to use real cases of hallucinations.

In addition to the mentioned corrective mechanisms , there are various procedures, for

detect hallucinations. However, there is no absolute certainty that sources of error can be avoided (Towhidul Islam Tonmoy et al., 2024). Albert-large-v2, for example, has made it possible to identify words with high entropy. It should be noted here that the detection mechanism only recognises words with high entropy, which is why a human-in-the-loop implementation cannot be neglected in terms of risk minimisation. Control mechanisms must also define processes that check the quality of the outputs.
To make this possible, validation platforms are being set up where employees can work together to check the quality of generative AI outputs.
This enables systematic risk prevention and the joint development of control mechanisms within the company. Integrating validation and verification platforms into everyday business operations not only supports the quality of outputs but also the trust of employees in generative AI.

The effective establishment of mechanisms and processes that minimise the risks of hallucinations when using generative AI can only be achieved with human-in-the-loop control frameworks. In this process, the AI takes the generated outputs and returns them to the human, who validates, checks or, if necessary, revises them. This human-in-the-loop process allows existing cultural problems, biases and malfunctions to be identified (Debnath et al., 2025). The study by Debnath et al. shows that participatory control mechanisms reduce the risks posed by bias and hallucinations and help to adapt generative AI to company-specific requirements. A practical approach to control mechanisms in companies is to form interdisciplinary teams that carry out quality assurance and ethical control of AI implementation. Furthermore, feedback processes must be implemented that enable employees to report errors or ambiguities in AI-generated texts. In addition, the implementation of a human-in-the-loop framework must be tailored to company-specific data and models. Expanding the human-in-the-loop process can increase the resilience of control mechanisms and shed light on blind spots in interactions with generative AI systems. Furthermore, continuous input from employees minimises the trust problem and serves as safety net.

In conclusion, this paper shows that identifying and minimising bias and hallucinations in human-machine interaction is a challenge for companies.
In addition to the risk of bias in generative AI outputs, the development and use of generative AI also carries the risk of hallucinations, in which AI systems produce false or fabricated

outputs .

The danger for companies is that the results generated by AI could be accepted uncritically by employees and thus lead to wrong decisions (Siebert, 2024).

These additional work processes are time-consuming and must be factored into employees' daily work routines. It is therefore essential for companies to implement governance systems that define responsibilities for quality control of AI outputs and derive measures. In addition, consideration must be given to the training employees need to understand mechanisms such as checklists, plausibility checks and feedback loops . Minimising bias and hallucinations in the day-to-day operations of companies is possible through various AI control instruments and in the area of word embedding applications, known as soft debiasing and hard debiasing. Furthermore, various retrieval-based corrective measures can also be used to reduce the risks of bias and hallucinations in generative AI outputs (Towhidul Islam Tonmoy et al., 2024). These retrieval-based corrective measures include mFACT, EVER and DRESS. The DRESS framework has improved the trustworthiness and honesty of generative AI texts. EVER has made significant progress in terms of quality by making corrections using retrieval of similar facts from other documents . In addition to technical adjustments to generative AI, the introduction of frameworks designed to reduce hallucinations requires, above all, employees who are able to use the control instruments. Employees must be able to recognise uncertainties and perceptions in AI outputs and decide when external sources need to be used for validation. Companies can provide assistance in this regard by providing guidelines. These guidelines show employees how and when to use the respective control instruments, how to interpret the results and what to do in terms of risk minimisation.

These guidelines are developed jointly with the departments concerned. With regard to training, care must be taken to discuss and consider real errors, hallucinations and examples with them and their employees. It is crucial to train and involve employees and to regularly update and further develop these training courses.

Although there are numerous and constantly evolving mechanisms for detecting hallucinations, a completely secure system for avoiding these systemic problems and context-related challenges will not be within reach in the future either (Towhidul Islam Tonmoy et al., 2024).

This is because albert-large-v2 can identify the words with the highest entropy. The

rest must be validated by the employees themselves in order to recognise what is correct or incorrect in the AI-generated texts. This is why continuous feedback and human-in-the-loop are necessary, i.e. the interaction of humans and machines for iterative improvement of the generative AI outputs. To this end, validation platforms must be created in which employees check the responses of AI systems.
In this way, employees play a significant role in identifying and filtering out incorrect facts or hallucinations. This has a collective benefit for employees, as it establishes a control mechanism within the company that is developed and monitored with and by them.
This means that all employees have their own control instruments to systematically ward off the accuracy of generative AI outputs, and it also improves confidence in AI implementation in company.

The risks associated with hallucinations from generative AI systems can be minimised primarily by implementing human-in-the-loop systems that ensure quality control in the respective area of application. These are control approaches for sustainable risk minimisation when using generative AI. Human-in-the-loop processes have proven to be a very efficient control mechanism that helps ensure that AI-generated texts meet the quality requirements of various cultural and corporate values. These approaches draw on both the contextual knowledge of employees and a variety of backgrounds and perspectives. The result is a heightened awareness and avoidance of risks generated by the systems, training data and algorithms (Debnath et al., 2025).
A participatory control process can help to minimise the risks associated with hallucinations, as these are reduced by the diverse backgrounds of the participants. They can help to compensate for the distortions of AI models and adapt to the needs of AI users. Employees ensure trust in AI systems. One control mechanism for minimising the risks associated with hallucinations in generative AI systems is to set up interdisciplinary teams responsible for quality control and ethical review of AI applications.
Another tool is feedback processes, which give employees a way to report deficiencies in generative AI output. The human-in-the-loop framework can also close the gaps in the existing human-in-the-loop framework for human-machine interaction by expanding cultural and ethical reflection capabilities in this system.

4.3 Data protection and compliance in everyday working life: awareness, options for action and limitations

Data protection and GDPR for generative AI tools such as ChatGPT pose a challenge in everyday business life. Often, guidelines and specifications for implementing data protection requirements are lacking, and companies are not sufficiently prepared. The case of the temporary ChatGPT ban by the Italian data protection authority illustrates the risk of lacking governance processes (CEDPO AI Working Group, 2023). There is also a considerable risk of non-compliance with personal data protection requirements if the data to be processed is not proactively anonymised, especially if the AI applications operate on unsecured data (Huchler et al., 2020).

Since the 1990s, it has been recommended that data protection be ensured through self-regulatory principles such as privacy by design and privacy by default. Nevertheless, in most companies, this only happens when forced to act after incidents become known (CEDPO AI Working Group, 2023). Employees are often unaware of the data protection implications and risks of generative AI, which can lead to incorrect data processing and the disclosure of personal data (CEDPO AI Working Group, 2023). Training and awareness programmes are necessary because the ability of employees to assess risks and raise awareness of how to handle confidential information is essential for the everyday use of AI tools. These training courses on data protection and the GDPR can reduce typical sources of error. One example of such sources of error is the publication of personal data by employees. This applies when training is offered in combination with information on specific risks posed by generative AI (Huchler et al., 2020).

The implementation of an awareness programme for both technical and organisational measures increases security within the company and employee confidence in AI. However, studies show that this is only happening in a few companies (CEDPO AI Working Group, 2023). It is therefore advisable to expand the programme by establishing data protection awareness as part of continuous personnel development and regularly adapting awareness training to new technological and regulatory issues and threat situations.

A feedback loop through a reporting and advisory channel for employees regarding possible data breaches would be a useful addition to the training. The effectiveness of security awareness programmes can also be increased with the technical implementation of privacy-by-design measures. The integration of anonymisation in cameras, document management systems or software can prevent data breaches.

(Huchler et al., 2020). These "on-board" protection mechanisms enable the AI tool to be used in a manner that complies with data protection laws and is also user-friendly. They increase user acceptance, as employees experience less uncertainty and fewer verification obligations in their everyday work. Furthermore, these systems are based on international standards for data protection, known as privacy-by-design principles, and thus adapt to an increasingly harmonised legal and regulatory situation (such as the EU AI Act).

However, technical privacy-by-design solutions alone are not sufficient and must also be integrated into awareness training and governance measures to ensure long-term data protection in AI-based systems. Above all, extending control mechanisms and feedback systems to employees enables proactive risk control and risk management.

The implementation of fixed roles and responsibilities as well as governance structures that regularly adapt to technological innovations and new legal frameworks is recommended (Protschky et al., 2024).

Furthermore, compliance and risk reports can serve as control measures in companies.

Another risk arises from a lack of technical expertise in data security and data protection among managers and users. This leads to inadequate implementation and understanding of data protection requirements and to a high risk of data protection incidents and GDPR violations (Brüggemann et al., 2025). This lack of IT skills must be compensated for through internal training.

A lack of internal compliance knowledge is exacerbated by the delegation of responsibility for data protection incidents to individual roles, departments or external service providers. This leads to a lack of awareness and expertise within the company, which in turn inhibits resilience and the ability to respond to internal risks. As a result, internal risks are difficult to control and influence. This situation could be prevented by introducing an interdisciplinary team tasked with managing all AI projects. This would also facilitate integration with business processes and risk management. In summary, it can be said that ensuring long-term data protection and compliance when using generative AI tools in German companies requires continuous investment in personnel, technology and organisation.

4.4 Efficiency gains and productivity vs. cognitive load

The use of generative AI tools can lead to efficiency gains and make work easier, but at the same time it can also contribute to impaired productivity due to increased cognitive load and multitasking. This section therefore examines how an optimal balance between the positive and negative effects can be found. This section is part of the overall analysis of the technical, human and organisational aspects of introducing generative AI tools in the German workplace.

4.4.1 Positive effects: reduced workload and increased efficiency

The use of generative AI such as ChatGPT and Copilot enables administrative and knowledge-based work efficiency by automating routine tasks. Generative AI can be used to support the creation of standardised reports and summaries or the research of information, allowing employees to focus on their creative and more complex tasks and increase their value contribution to the company (Löll, 2024; Majkovic et al., 2024). While routine tasks can be successfully outsourced, the validation of generated results requires user control. Automating certain routine tasks does not replace human control and merely leads to an increase in efficiency through the delegation of these tasks.

Empirical evidence shows that the use of generative AI in text generation and data processing leads to a subjective perception of reduced workload, which contributes to increased job satisfaction (Löll, 2024; Morlock et al., 2025). The scalability of generative AI enables multiple tasks to be processed in parallel. The question remains whether this is actually a relieving factor for employees or whether additional activities arise that are attributed to the management and control of AI processes .

Generative AI in university administration and product development can be seen as an enabler for organisational innovation (Majkovic et al., 2024; Morlock et al., 2025). The case of a university illustrates an increase in efficiency, as generative AI was used for documentation or verification. The case of product development shows that work efficiency depends on the respective infrastructure of the work and the employees, which in turn requires coordinated processes. In this case, it becomes clear that the coordinated introduction of generative AI is essential for achieving an increased efficiency .

One advantage of generative AI is its potential for personalised text creation (Löll, 2024). Employees can use the tools to create individualised text templates that are of high quality and consistency. The possibility of personalisation is particularly important in customer contact of work results is crucial.

The use of generative AI makes it possible to carry out work processes independently of location. For employees, especially those of Generation Z, this leads to a subjective increase in the flexibility of their work organisation (Majkovic et al., 2024). The possibility of location-independent work increases flexibility in work design and provides relief. However, the increased flexibility is heavily dependent on the organisational framework conditions, which uncertainty human-machine interaction minimise as much as possible.

The automated comparison of results generated by generative AI and the complementary tasks performed by employees (e.g. checking and validating results) minimise the risk of errors (Majkovic et al., 2024). Studies show that 79 per cent of employees check AI results to ensure their quality and correct errors. This "human-in-the-loop" approach improves work results and confidence in AI.

In addition, the use of cross-departmental governance mechanisms promotes acceptance of generative AI in everyday work (Protschky et al., 2024). When governance mechanisms exist within an organisation, employees experience increased satisfaction. Companies that have already implemented these mechanisms observe higher employee acceptance of generative AI use. These mechanisms should be supplemented by awareness-raising and training measures, which should be strongly oriented towards the prior knowledge of employees (Morlock et al., 2025). For generative AI to be successful, it is clear that governance, competence building and participatory control must be combined in order to achieve comprehensive value creation through generative AI and not exclude employees (Protschky et al., 2024; Morlock et al., 2025).

4.4.2 Negative effects: multitasking, distraction and cognitive load

The negative effects of using generative AI tools include increased cognitive load and multitasking, which arise from the control tasks required by the implementation of these tools. This is because the use of generative AI forces employees to check and evaluate whether the AI is delivering appropriate and plausible results. This leads to increased mental effort, especially since generated AI content can contain errors in up to 20 per cent of cases, which cannot be detected immediately (Joshi, 2025). This is particularly stressful for less experienced employees, who often have less developed skills to distinguish useful AI-generated content from content that contains errors (Al Haque et al., 2025). The cognitive fragmentation

caused by the continuous control process has an impact on job satisfaction and perceived control (Joshi, 2025). Nevertheless, organisations have few, well-developed measures in place to systematically relieve the burden on employees (Kaltenbrunner & Henne, 2024). Furthermore, notifications and system warnings sent by generative AI tools are additional stress-inducing factors.
Particularly in health and administrative fields, professionals report a phenomenon known as "alert fatigue," i.e., sensory overload caused by frequent and excessive warnings. This leads to a reduction in attention when warnings are seen, which in turn increases the likelihood that relevant errors or problems will not be detected (Kaltenbrunner & Henne, 2024). In addition, the constant messages cause a distraction from the actual creative and demanding tasks, which reduces productivity. However, there is a lack of detailed configuration settings for warning thresholds that would allow differentiation between important and less relevant warnings.

Empirical evidence shows that too many notifications reduce acceptance in organisations . (Kaltenbrunner & Henne, 2024).

Furthermore, modern generative AI systems, such as ChatGPT and Copilot, often generate erroneous and fictitious content, known as "hallucinations," which are difficult to recognise as such because they are stylistically flawless (Joshi, 2025; Mallette, 2024). This makes it necessary to verify and check the generated content at all levels and in all work contexts, which in turn requires constant switching back and forth between creative and control-oriented tasks. This inevitably leads to a greater expenditure of time and a shift away from the original tasks. Furthermore, the increase in control effort will negatively affect trust in generative AI tools, thus further intensifying the verification of AI-generated results. This vicious circle leads to overload, frustration and a decline in productivity (Joshi, 2025; Mallette, 2024). Another area of tension exists between the promised relief that generative AI tools offer and the actual additional workload they can entail.

Employees often report feeling relieved when using generative AI tools such as Grammarly or Copilot. However, empirical studies have shown that the additional working time required by employees to review, edit and correct AI results relativises the actual relief provided by generative AI tools (Mallette, 2024; Al Haque et al., 2025). Less experienced employees report the advantages offered by generative AI. However, they also describe how interacting with generative AI tools and checking generated results creates additional stress and thus leads to a shift in workload towards complex, cognitive tasks (Al Haque et al., 2025). In practice, companies do not take sufficient account of the fact that the actual additional workload resulting from the implementation of generative AI tools in companies relativises their perceived usefulness.

Furthermore, the increased complexity is often not reflected in traditional models of working time organisation that have been used to date (Mallette, 2024). Furthermore, the use of generative AI tools means that control and verification tasks must be established as new core competencies that address the ever-growing complexity of generative AI outputs (Al Haque et al., 2025; Joshi, 2025).

In order to cope with constant interruptions to work and various warning messages in the production process, employees must have the ability to learn quickly, adapt to new ways of working and deal with stress in order to reduce the additional burden caused by through generative AI tools , to (Joshi, 2025). In order to improve employees' competence in the area of control, continuous training is required that reaches all employees and prepares them for interaction with new technologies. This is because certain professions have low technological competence (Kaltenbrunner & Henne, 2024). Human-in-the-loop systems and adaptive interfaces enable interaction between employees and technology to prevent errors, facilitate the verification of AI results, and promote the development of resilience and technical expertise (Joshi, 2025; Kaltenbrunner & Henne, 2024). In the area of organisational control processes, resilience programmes are central measures for preventing overload among employees .

In summary, it can be said that the implementation of generative AI tools in companies brings relief for employees, but also leads to a number of new, stress-inducing burdens due to the increased complexity of generated AI outputs.

4.5 Shifts in skills: upskilling/reskilling and de-skilling

The implementation of generative AI such as ChatGPT and Copilot is increasing the participation of German employees in upskilling and reskilling. Technological innovations are a key driver of strategic continuing education initiatives. On average across the studies, 46 per cent of employees participate in upskilling and 27 per cent in reskilling (Eilers et al., 2025). This shows that

Companies must respond not only to technological changes, but also to changes in skills requirements. However, the question remains as to whether existing measures are sufficiently tailored to meet the diverse learning needs of the workforce. The strategic outlook for securing employability through further training plays a central role in skills development in the context of generative AI. Skills gained through generative AI are linked to new areas of responsibility generated by digitalisation. Critical monitoring of AI expenditure is one of the basic digital skills required in the labour market (Eilers et al., 2025). Meta-skills in dealing with technology are also more important than purely technical (Körner et al., 2019; Headecke et al., 2023). But to what extent is it possible to develop meta-skills that meet demand through continuing education?

Companies are increasingly using the development of AI skills to retain employees and their development. Learning formats and adaptive training platforms enable flexible design of the continuing education system (Eilers et al., 2025). It is therefore clear that continuing education also requires constant technological and methodological development in order to meet growing demands. However, it should be critically questioned whether companies can validate the learning success and effectiveness of these measures in the long term. Due to the automation of routine tasks and the use of generative AI tools, there is also a risk of de-skilling. In this case, tasks performed by AI can render previously required skills unnecessary (Reinmann, 2023). Just as industrialisation and digitalisation turned skilled work into controllable activities, the use of AI tools can lead to a similar development. This could result in work becoming increasingly reduced to the control of outputs. As a consequence, the practical experience and repertoire of actions of employees could diminish. Over time, the execution of tasks by generative AI tools also leads to a gradual loss of skills. This happens because one's own routines for action, which consist of problem solving, critical reflection and decision-making, are interrupted (Reinmann, 2023).

Employees who merely check AI outputs would therefore feel the impact of routines even more profoundly. As a result, they would become disconnected from the actual content of their work in the long term and could less less identify with their work. This makes it clear that companies must strive to implement activities when developing work processes that involve the use of generative AI. These should the workers themselves carry out and not merely check.

Another concern is that generative AI will act as a driving factor in the digital divide and skills polarisation, marginalising people with little affinity for technology

(Reinmann, 2023; Brynjolfsson et al., 2023). Companies should therefore pursue an inclusive approach and, when providing further training, also pay attention to those employees and employee groups who have difficulties in dealing with technologies .

De-skilling is contrasted with upskilling. Studies report that less experienced employees make the most significant gains in productivity. AI-supported assistance technologies can enable them to match the skills of more experienced team members after only a short time (Brynjolfsson et al., 2023). In terms of upskilling, the use of generative AI can therefore lead to an enormous acceleration of learning processes .

By learning and applying new digital ways of working, the workflows of those with little experience are accelerated. This enables them to take on more demanding tasks based on knowledge that was previously inaccessible to them (Brynjolfsson et al., 2023). This speeds up the onboarding of new employees and can thus improve the innovative capacity of companies. Such developments can also be attributed to the interaction between AI tools and people in hybrid teams. The use of hybrid forms of teaming in combination with the provision of ongoing feedback contributes to more effective knowledge and skills management in technological context .
One of the most significant changes brought about by the use of generative AI is the shift in competence-related requirements.
The skills required are shifting from operational to critical-conceptual execution (Körner et al., 2019). In future, employees will increasingly need to be able to assess uncertainty evaluate and and master the challenges associated with this.

Overcoming these challenges, which are often treated as meta-skills in the context of technology, is crucial to the success of the division of labour between humans and AI, but only difficult to teach.

Companies must therefore implement organisational qualification programmes, as the problem of unavailability of the required skills may arise during implementation. This is also due to the fact that the level of knowledge and expertise relating to AI is still limited, meaning that employees cannot draw on an existing repertoire of work routines and techniques (Körner et al., 2019). Flexible learning structures with needs-based modules are therefore necessary to build the required level of competence. The implementation of organisational learning formats could also accelerate the learning curve of employees and , according to , enabling faster competence development .

In addition, companies should expand peer learning as a tool for knowledge transfer and it with other forms of training and continuing education .

Furthermore, testing and verification procedures are essential to ensure that the necessary skills are developed and to avoid overburdening employees (Headecke et al., 2023). Repeatable skills tests, output validation and validation measures in AI systems are becoming increasingly important in this context. The higher the level of assurance required, the more in-depth the validation measures will have to be, because the probability of error should be as low as possible, especially in safety-relevant and knowledge-intensive processes. The systematic validation of AI systems and newly acquired skills also ensures that there is no loss of knowledge or

For the practice recommend we, use the following testing methods to : – Checklist for self-assessment by employees – Continuous learning through feedback from AI tools – Qualitative and quantitative control through supervision

We consider it best practice against shifts in competence when knowledge transfer between humans and AI is reciprocal and competence management is ensured through validation.

4.6 Autonomy, control and monitoring in the work process

The introduction of generative AI tools has a significant impact on the autonomy and control of employees. Most generative AI tools work algorithmically and are designed to automate many previous tasks, thereby developing a control mechanism. Work instructions and processes are specified, which significantly restricts the employee's own scope for action. This results in external control, and many decisions that would normally be made by the employees themselves are left out of the equation (Krieger et al., 2025). A study by Huchler et al. (2020) also concludes that AI increases performance control and monitoring of employees. This development brings many new forms of control . . The activities of employees in the company are increasingly being monitored, behaviour and work results are being measured, and performance is being controlled. This development brings AI surveillance to the fore, and employees are becoming heavily involved in the work process through controls. This harbours considerable potential for

Optimisation and error reduction in operational processes. On the other hand, however, this leads to employees feeling this pressure of surveillance and tending to feel controlled by external forces , than themselves . . Despite all the automation of employees, around 75% of them still expect humans to continue to be the decision-making and controlling authority for the results of AI . (Krieger et al., 2025). Nevertheless, the monitoring of AI itself is characterised by a control aspect that employees must keep in mind. Due to the increased use of AI, this responsibility is transferred to employees, who must take over the controls and monitoring. Employees are responsible for controlling the technology so that it runs within the specified parameters and does not develop its own. This is particularly difficult when the control and monitoring system is not very transparent. For this reason, employees must undergo training in advance and acquire in-depth knowledge of AI .

In particular, multitasking can be an obstacle, as employees in many industries are forced to do so. This phenomenon is widespread in many knowledge-based fields, such as healthcare and research. It is often assumed that AI monitors employees and that they no longer need to exercise any control themselves. However, the opposite may be true, and this assumption could be far from reality. Kaltenbrunner & Henne (2024), for example, note that employees are particularly stressed by AI monitoring. As employees generally face very high demands in their work, misinterpretations and a certain degree of "alert fatigue" often occur. The system's warning systems and messages can generate a huge number of notifications that many employees are no longer able to process. These messages are not always of crucial importance, which makes it difficult for employees to often ignore them .

A study by Huang et al. (2025), for example, shows that AI control and monitoring systems can exhibit algorithmic hallucinations and distortions. This means that errors and incorrect answers are often inevitable. In order to strengthen trust in the systems, employees must be able to recognise and eliminate such errors in decisions. Increased monitoring is also necessary because employees do not know exactly how the AI tool works and how decisions are made. Transparency must be improved in this area. It is also possible that the systems may discriminate in their responses, which must also be recognised and corrected by the employee .
Many scientists are concerned that humans will become less important as a result of

Development and the use of AI systems. A balance must be struck between technological control and human autonomy. Control by AI leads to a loss of meaning in one's own skills at work and there is a risk of "de-skilling" (Krieger et al., 2025; Huchler et al., 2020; Kaltenbrunner & Henne, 2024; Huang et al., 2025). Care must be taken to ensure that the demands placed on employees do not relate solely to the control and monitoring of AI technology, thereby negating the value of their original expertise at work. Research shows that participatory models and "human-in-the-loop" approaches are needed here to secure employees' decision-making and action rights and to make meaningful use of the potential of generative AI tools.

4.7 Comparison by field of application

The use of generative AI tools such as ChatGPT and similar programmes in knowledge-intensive industries such as research, technology and communication focuses primarily on text generation, ideation and knowledge management. This significantly increases work productivity (Al Naqbi et al., 2024). The use of generative AI in these areas is already highly valued, as the creation of personalised texts is more time-saving and less labour-intensive than manual editing. In addition, AI-based suggestions can serve as a basis for new and creative ideas (Al Naqbi et al., 2024). However, the question should be asked to what extent the heavy use of AI-generated content can impair the independence and critical thinking of employees. Studies that examine these effects on employee skills are to to date . still

When generative AI is introduced in manufacturing industries, such as the automotive sector, it generally supports activities and processes associated with manual production. It also promotes the skills of employees (Link & Hamann, 2019). Flexible adaptation of the system to work processes and qualifications is of particular importance.

Work organisation and socio-technical challenges must be taken into account equally in order to avoid possible rejection and excessive demands on employees (Link & Hamann, 2019).

It is important to critically examine whether the desired growth in skills is offset by increasing control of employees and a loss of autonomy. It would also be interesting to investigate how the use of generative AI in manufacturing industries affects the working atmosphere and the motivation of employees . When implementing data protection measures and governance approaches in German companies , , , , , , , , and technology companies and the manufacturing sector. Service and technology companies have sophisticated data protection concepts and processes for employee participation, while the manufacturing sector has considerable ground to make up in this regard (Hubel et al., 2024). In knowledge-intensive industries where the use of AI tools from unauthorised sources is widespread, there is a higher risk of data breaches. Without alternatives being offered, employees resort to using private accounts out of necessity (Krieger et al., 2025). Manufacturing companies, on the other hand, tend to be characterised by systematic pilot projects and a restrictive approach to implementation. Governance guidelines are generally stricter in these industries (Link & Hamann, 2019). These differences raise the question of cross-industry approaches to governance management. In addition, employees should not just be "taken by surprise" by such guidelines, but should participate in their design .

AI-based applications can influence skill development to varying degrees. Depending on the area of application and the degree of automation, there is a shift in the main activity from routine tasks to review and control (Krieger et al., 2025). This leads to de-skilling effects. On the other hand, generative AI is used to expand human skills by supporting employees in analysis and problem solving in creative or specialist knowledge-related activities. Empirical data shows that 57% of AI applications focus on skills expansion and 43% on task automation (Krieger et al., 2025). What needs to be adjusted in current training and continuing education programmes so that they are optimally adapted to the respective industries and types of work? The better continuing education is tailored to the different needs of the workforce, the more efficient it is and the more likely it is to have a positive effect on the workforce and individual companies (Hubel et al., 2024). When dealing with bias, hallucinations and the monitoring of generative AI in companies, different challenges also arise depending on the type of industry. In highly regulated sectors, such as finance or healthcare, the likelihood of unsatisfactory or even incorrect results is significantly increased. This is because the risk of legal and ethical consequences is more serious in these sectors (Hubel et al., 2024). This makes it all the more important for employees in these industries to have a strong ability to detect and correct errors and to pursue a human-in-the-loop strategy (Krieger et al., 2025). In less heavily regulated, creative professions, correcting faulty content is not such a high priority, but is rather seen as an opportunity to generate novel solutions and ideas (Al Naqbi et al., 2024). Nevertheless, a mechanism for detecting bias and hallucinations is essential in any work environment in order to be able to deal with them subsequently. The necessary support for this in all areas of the company, from the IT department

from the organisational structure to the employees, should definitely be provided. This also strengthens trust and confidence in dealing with the new technology. To what extent can this support be offered and maintained in the form of training courses?
An increasingly difficult problem with the use of AI in German companies is that the use of AI tools that are not provided by the company, e.g. in technical and engineering industries, is becoming more and more widespread. This trend poses a number of data protection and compliance risks, as it involves the use of private access to uncontrolled AI platforms (Krieger et al., 2025). This problem raises questions about the extent to which this phenomenon is widespread in German companies and what risks it poses. Companies that take a more restrictive approach to technology adoption, with systematic pilot projects and subsequent approval, are considered less insecure. To what extent do employees feel more secure when AI applications are only implemented after lengthy evaluation phases, and is this perceived increased security justified?

Digital assistance systems in manufacturing industries are primarily responsible for combining short-term productivity increases with sustainable skills development for employees (Link & Hamann, 2019). They make it easier to tackle complex tasks and promote the ongoing optimisation of work and learning processes. Fundamental to their success is the ability to adapt quickly and flexibly to changing working conditions and new skill requirements. Unlike in other knowledge-intensive industries, this is of considerable importance in industrial production because it supports short-term adjustments, is not solely focused on maximising efficiency, and incorporates the optimisation of work and learning processes. Companies are also counting on the use of this technology to contribute not only to short-term productivity gains, but above all to a sustainable expansion of employee skills (Link & Hamann, 2019). To what extent do work processes need to be redesigned to ensure acceptance among the workforce and prevent excessive demands being placed on them as a result of the introduction of generative AI tools?

The different areas of application clearly show that the advantages, but also the challenges, for employees can vary significantly depending on the industry and field of activity.

5. Discussion

The importance of theoretical classification and practical solutions becomes clear in the following sections. To this end, continuing education strategies, governance and human-in-the-loop are discussed and, in some cases, examined to determine how they can help unlock the full potential of generative AI and thus reduce risks. This paper thus builds a bridge between theory and practice, which is essential for sustainable implementation. This reflection serves as the basis for the final assessment and concrete recommendations for action.

The results of the literature analysis (n = 10) can be classified as follows based on theory: In the Job Demands-Resources Model, generative AI tools increase structural and personal resources (e.g., automation, access to knowledge), but create new demands (validation effort, additional interfaces). In the UTAUT/TAM framework, performance and effort expectancy have an ambivalent effect: efficiency gains are offset by uncertainties regarding data protection, quality control and role change. From a human-AI teaming perspective, shared responsibilities, transparency and error-catching mechanisms determine the quality of results; if these are lacking, cognitive load and risk of error increase. This classification explains why bias/hallucination, data protection/compliance, cognitive load/efficiency and shifts in competence occur as related problem areas – and why countermeasures at the user level (prompt routines, dual control checks, governance no-gos) are central.

5.1 Classification of problem areas in existing theories

The application of the Job Demands-Resources Model (JD-R) in the context of generative AI technologies illustrates the dialectic between resources and demands. Generative AI tools generate a resource effect because they can eliminate routine tasks, thereby contributing to increases in efficiency and innovation (André & Bauer, 2019). On the other hand, they also generate demands through control and validation tasks, as employees have to check AI outputs for bias and hallucinations (Huchler et al., 2020; Hubel et al., 2024). Due to the increase in the complexity of tasks, this can also lead to additional workloads, which ultimately result in stress and overload for employees. Several empirical studies show in this context that the use of human-in-the-loop approaches and further training can be helpful as measures for stress prevention (André & Bauer, 2019). It is clear here that the demands and resources in everyday working life are not balanced solely by the use of generative AI tools, but must be actively managed by organisations. Therefore, a dynamic expansion of the JD-R model to include intervention options with a focus on technological and human resources could make a contribution. For example, intelligent feedback systems or awareness programmes on topics such as data protection or bias could support a sustainable increase in work productivity while taking into account the well-being of employees (Butollo et al., 2024; Huchler et al., 2020).

The paradigm of skill-biased technological change supports the classification of the requirements set for employees. It shows that generative AI tools perform repetitive tasks and that the requirements for higher-level skills such as critical thinking or validation are increasing (André & Bauer, 2019; Huchler et al., 2020). On the one hand, this leads to upskilling and reskilling requirements, while employees who perform simple tasks are threatened with de-skilling. The literature shows that employees with little experience and low formal qualifications can benefit from this upskilling in the short term. This happens when AI systems support them in more complex tasks, making them easier to complete. More experienced and highly qualified employees tend not to benefit from generative AI, as their problem-solving skills are reduced unless they train them (Crowston & Bolici, 2025). Organisations are faced with the task of designing training programmes for AI tools in order to develop technological and meta-competence-related skills. At the same time, it is crucial to take into account the different needs of the workforce in these programmes in order to prevent alienation and division. A critical assessment of skill-biased technological change makes it clear that it should not be seen as an inevitable development. Rather, it should be viewed as a malleable process in which the focus is on developing skills and innovation potential. Participatory training concepts could help to secure the employability of the workforce and create added value in the form of innovations. .

In connection with generative AI, the importance of the Technology Acceptance Model

"Technology Acceptance Model" (TAM) and "Unified Theory of Acceptance and Use of Technology" (UTAUT) should be further expanded. Both models describe the importance of perceived usefulness and user-friendliness for the successful implementation of AI technologies (Brynjolfsson et al., 2023). However, the increase in uncertainty and mistrust due to risks such as bias, hallucinations or lack of transparency indicates that common models for explaining the acceptance of technological innovations need to be expanded. These risks can lead to limited or incorrect use of the technologies and thus to damage to reputation (Protschky et al., 2024). A critical point is that there are currently only a few companies in which responsibilities and overarching systems are being established to create acceptance for generative AI. This master's thesis assumes that acceptance indicators must be expanded to include new dimensions that address the specific set-up of generative AI in order to understand the acceptance processes of AI applications.

In addition to dimensions such as data protection, compliance and co-determination, trust in the automation of decisions and the perception of algorithmic fairness could be integrated into the models as additional acceptance indicators in order to make them more robust and applicability applicability to generative AI to .

The theory of human-AI teaming, which describes how a partnership between humans and AI systems can be established in organisations, is not currently being put into practice in companies. Generative AI tools are used to prioritise tasks based on algorithms and monitor the work of employees (Al Haque et al., 2025; Huchler et al., 2020). On the one hand, this can increase employee output and reduce errors, which in turn makes the organisation's work more efficient. On the other hand, employees could lose control over the automation of decisions and the completion of their tasks, meaning they are only used to validate and review the results. This puts pressure on employees and can lead to de-skilling in the long term. Furthermore, it is paradoxical when generative AI systems make decisions automatically, but at the same time humans are called upon as a control authority to detect algorithmic errors. This increases the burden on employees. Therefore, successful human-AI teaming can only work in the long term if governance and skills development are not considered separately, but rather if employees are actively involved in the management and control processes. In a purely supervisory relationship, employees are demoted, which negates the effects of automation and thus creates a competitive disadvantage . .

Theories on data protection in organisations with reference to co-determination and governance are becoming increasingly relevant for employees with the introduction of generative AI. Regulatory requirements, such as those from the GDPR, have an impact on the technical and organisational framework conditions for the use of generative AI. This also influences acceptance by employees (Protschky et al., 2024). Employees must trust the provisions of data protection guidelines and become unsettled if the level of data protection is unclear or insufficient. Furthermore, the co-determination rights of the workforce play a role in generating acceptance and are supplemented by participatory governance processes that serve the implementation of generative AI (Huchler et al., 2020). This paper examines the data protection paradigm and the influence of co-determination on the acceptance of generative AI in the context of participatory organisational development. Employees should not be limited to purely executive processes, but must be actively involved in the design of guidelines in order to exemplify data protection and compliance. In order to involve these employees in the design process, they can be explicitly trained as data protection experts in training programmes. In addition, members of the organisation are appointed as representatives and supported in the exercise of their duties.

Governance models that take into account not only regulatory aspects but also operational challenges at the employee level can strengthen trust of employees in the technology. In conclusion, it can be said that by classifying the identified problem areas into the various theories, it becomes clear that the use of generative AI in organisations has far-reaching implications for the working world. Therefore, further development of the theories and classification of the insights derived from them are necessary in order to exploit the potential of generative AI tools and limit risks.

5.2 Solution options: further training, governance and human-in-the-loop

Targeted further training for employees is essential in order to adequately deal with the risks and challenges posed by generative AI tools, such as bias and hallucinations. Training content must focus on the systematic review and correction of AI outputs. In addition, users must be able to recognise discriminatory and factually incorrect results (Aschemann et al., 2025). The type of training offered must be critically examined, as there are differences in prior knowledge, technical affinity and areas of responsibility (Gkintoni et al., 2025). General forms of training do not adequately address the individual needs of employees. In addition, motivational and emotional aspects must be taken into account, as fears and misjudgements can have a negative effect on the learning process and lead to a counterproductive attitude towards AI tools (Aschemann et al., 2025). To counteract this problem, modern methods such as WEAT or MAC are suitable for analysing algorithmic biases and promoting critical reflection among employees. To ensure effective, adaptive and lifelong learning, training measures must be regularly updated, as AI applications are developing rapidly (Gkintoni et al., 2025).

Practical knowledge transfer through hands-on training, simulations and human-in-the-loop interaction mechanisms is an important addition to effective continuing education programmes that teach new skills. Simulating real work scenarios with AI tools introduces employees to the role of the supervisory authority and raises awareness of their responsibilities. In the context of AI-supported processes, many employees see themselves as ultimately responsible for reviewing and validating AI outputs. If employees are not prepared and have not grown accustomed to the complexity of AI applications

, this to to overwhelm them.

The introduction of organisation-wide governance rules can promote the acceptance of generative AI applications, ensure compliance and contribute to the successful, sustainable introduction of technology. If responsibilities, tasks and duties are clearly regulated and defined, this can help to reduce uncertainty and friction among employees (Protschky et al., 2024). The introduction of cross-company governance rules is also of great importance in order to minimise the risks of faulty AI decisions and data security breaches. Ideally, governance rules are controlled technically and organisationally (Protschky et al., 2024). Employees must always be involved in the introduction of new rules, as a lack of co-determination leads to acceptance problems and inhibits the company's ability to innovate. Monitoring and regular feedback on AI malfunctions are essential aspects of working successfully with governance rules. In addition, industry-specific characteristics must be taken into account, as the regulatory risk profile of manufacturing companies and knowledge-based companies varies (Hubel et al., 2024). Last but not least, the adequate qualification of governance managers plays an important role. In addition, existing management systems must be adequately adapted to the uniform European AI regulation (Aschemann et al., 2025; Protschky et al., 2024).

Human-in-the-loop approaches are a suitable means of minimising erroneous or unfair AI decisions and ethical risks. These approaches ensure that human expertise can be utilised (Gkintoni et al., 2025; Protschky et al., 2024). The HITL concept combines working with AI applications with the expertise of employees and contributes significantly to building trust, transparency and fairness in AI systems in sensitive industries (e.g. healthcare and education). The technology-assisted review of AI decisions also enables the rapid identification of error causes, which contributes to adaptive learning processes. However, the implementation of HITL concepts implies the definition of specific competence profiles and roles for employees who act as reviewers and controllers. In addition to technical knowledge, communication skills and a high level of ethical sensitivity are particularly relevant for this. Furthermore, companies must have the ability and willingness to identify new processes and risks through continuous evaluations to identify (Protschky et al., 2024). The AI Regulation can be used for the systematic empowerment of employees in dealing with generative AI. Companies must take comprehensive measures to achieve general skills growth and improve AI competence (Aschemann et al., 2025). Continuing education measures must be modular in design and integrate various learning programmes. The measures include basic skills and advanced skills in algorithm transparency, data accuracy, bias detection, data protection and ethical considerations. The AI Regulation also provides for the regular revision and updating of training materials. This is necessary in order to keep pace with the increasing availability of more and more AI models and new findings regarding errors, vulnerabilities and ethical risks. This leads to a change in the risk or AI deployment profile within the company (Aschemann et al., 2025).

In addition, the AI Regulation aims to ensure that employees working with AI applications are not only passive consumers of the technology, but also active producers .

In order to reduce cognitive overload among employees, technologies must be integrated that offer personalised assistance and continuously adapt to the individual learning and knowledge levels of employees. AI technologies analyse employee performance and continuously adapt the assistance provided to the performance level (Gkintoni et al., 2025). With neuroadaptive technologies, which record and analyse neurophysiological data (e.g. EEG, fNIRS), tasks automatically become easier or more difficult when employees are overwhelmed. Technical monitoring instruments should always be linked to human feedback.
Multimodal feedback systems enable adaptive support across different skill and stress levels. Such adaptive technologies reduce overload, the risk of alert fatigue during control and validation activities, and promote job satisfaction and acceptance of AI (Gkintoni et al., 2025). Furthermore, the technologies contribute to long-term competence development and reduce de-skilling, dependency and the risk of digital anxiety among employees.

5.3 Implications for companies and employees

The lack of control by companies in dealing with generative AI leads to uncertainty and rejection among employees. In addition, the lack of control causes additional costs for employee training and organisational adjustments (Protschky et al., 2024). There is also a risk of incorrect/flawed implementation when standardising data protection regulations, transparency and responsibility (Protschky et al., 2024). A lack of control also leads to the use of unauthorised generative AI tools such as ChatGPT, which poses risks in terms of compliance (protection of data and information, GDPR) (Krieger et al., 2025). It can also trigger rejection of generative AI tools, as employees do not understand their purpose and how they work (Hubel et al., 2024). Uncoordinated implementation of generative AI systems can lead to redundant work and a resulting reduction in innovative strength (Protschky et al., 2024). The acceptance and trustworthiness of generative AI tools are influenced by the fact that employees are aware that the results of these tools still contain errors or uncertainties and that the generated content cannot simply be adopted (Majkovic et al., 2024).

Furthermore, ongoing training and further development are needed to address the critical risks of bias, hallucinations and technical uncertainties of generative AI tools, as well as the challenges of quality assurance in relation to the implementation of generative AI (Aschemann et al., 2025; Gkintoni et al., 2025).

Generative AI tools make work easier for employees by automating repetitive tasks, but at the same time they also bring new requirements in terms of control, multitasking and critical questioning of generated content (Hubel et al., 2024). The need to constantly check AI outputs also carries the risk of so-called "false positives", where the AI identifies a potential deviation that does not actually exist. This places an additional burden on employees and is often referred to as "alert fatigue" (Kaltenbrunner & Henne, 2024). Other problems with generative AI tools include working with AI-based and manual tasks simultaneously (Mallette, 2024), the increasing risk of context switching (Kaltenbrunner & Henne, 2024), and multitasking (Mallette, 2024).

Algorithmic management systems often take away employees' autonomy and, through algorithmic controls, bring the pressure of surveillance into companies (Huchler et al., 2020). Although these algorithmic systems increase employee productivity, they also restrict their scope for creativity and control (Krieger et al., 2025). In such cases, employees often see themselves as merely playing a supervisory role for the AI (Huchler et al., 2020). In addition, algorithms form the basis of many decision-making processes, meaning that over time, employees may no longer be making necessary decisions themselves and may lose their decision-making skills in the long term (de-skilling) (Huchler et al., 2020)Furthermore, employee trust in new technologies such as generative AI must be maintained. This is best achieved through human-in-the-loop or human-in-the-centre models and employee co-determination rights (Hubel et al., 2024; Protschky et al., 2024). Generative AI tools are used in different ways in different areas of the company. In the area of knowledge work, unauthorised generative AI tools such as ChatGPT are used in most cases due to a lack of company-owned AI applications.

This creates increased agility in innovation, but can lead to compliance, control and liability risks (Krieger et al., 2025; Hubel et al., 2024). In manufacturing companies, on the other hand, AI tools and their use have been centrally controlled as pilot projects, with appropriate governance mechanisms implemented to reduce risks; However, this often results in a loss of innovation (Hubel et al., 2024). Both areas show that tailor-made measures are necessary for employee training and the management of generative AI tools in order to meet technological, cultural and regulatory requirements (Majkovic et al., 2024; Protschky et al., 2024).

5.4 Limitations of the work and research perspectives

Empirical research from an employee perspective on the use of generative AI tools is still limited. There is a lack of knowledge about psychological stress, loss of control and shifts in competence. Many studies only consider the introduction of AI from an organisational or technical perspective. Topics such as stress, uncertainty or metacognitive competence development in human-machine interaction are rarely addressed. The effects on the role of experts or resilience in the event of misconduct remain unexplored (Hubel et al., 2024; Kaltenbrunner & Henne, 2024). Due to increased digital validation and the associated changes in everyday working life, future studies should focus on individual stress profiles, motivation and the promotion of resilience. Industry-specific differences in governance, data protection, or the acceptance and integration of generative AI tools are known, but are often only mentioned superficially and unsystematically. For example, knowledge-intensive industries increasingly have problems complying with rules when using unauthorised AI tools. Meanwhile, manufacturing industries tend to work with test projects with increased control, but in significantly shorter innovation cycles (Hubel et al., 2024). There are no systematic research efforts regarding the influence of company size, corporate culture and regulation. This could be analysed through industry comparisons and case studies to identify industry-specific risks and opportunities as well as appropriate governance and training strategies. There is no empirical research on the question of integrating generative AI tool governance frameworks into existing governance and control models. For example, various multi-level models, such as the Generative AI Governance Framework, are described. However, there are no studies on integration with other control systems, such as COSO, or standards such as compliance guidelines (Emett et al., 2023). There is also a lack of studies with examples of successful governance structures that are linked to the various framework conditions . .
This could zum Beispiel durch die Zusammenführung von Governance-System und

Corporate culture must be brought together and related to personal stress factors. In addition, there is a lack of empirical research with best practices and industry-specific solutions regarding data protection and co-determination with regard to the European AI Regulation, which requires companies to implement governance processes .

The question of whether and how generative AI tools can be used efficiently without increasing cognitive stress has hardly been investigated to date. Findings from studies in medicine suggest that control and validation processes in particular can lead to so-called "alert fatigue" and thus significantly increase mental stress (Kaltenbrunner & Henne, 2024). The lack of empirical research also relates to the effects on motivation, job satisfaction and mental health. The influences on professional identity, the development of coping strategies and the feeling of being useful are also unknown. Future studies in various industries and companies of different sizes should focus on investigating these stresses and creating opportunities for prevention that will lead to increased acceptance of generative AI in work processes .

The ethical and social consequences of algorithmic controlling and the participatory effect of human-in-the-loop are discussed extensively in theory, but not broken down into everyday working life. Reducing the loss of control, increasing trust through co-determination, and increasing human control in human-in-the-loop processes, thereby promoting expertise and avoiding de-skilling through adaptive control processes, are key questions that need to be answered (Hubel et al., 2024; Kaltenbrunner & Henne, 2024; Emett et al., 2023). Differences in the effectiveness of human-in-the-loop strategies across different industries or company sizes have also not been identified. There is also a lack of measurable indicators to represent autonomy, ethical sensitivity and user acceptance. Future studies should examine the interactions between governance models, participation and individually experienced control in more detail in order to be able to identify recommendations for action for integrating such approaches into practice.

In practical terms, this means lightweight governance (unilateral do/don't guidelines on PII, source references and approvals), two-stage training (basics: hallucination/citation check; advanced: prompt design, chain controls) and human-in-the-loop audit trails for quality-sensitive tasks.

Effectiveness can be observed using a few KPIs: error rate in AI outputs, review time per task, proportion of checked AI results, data protection incidents per period, and training hours on prompting/validation. This achieves efficiency gains without shifting validation efforts and compliance risks to employees.

In summary, it can be said that there are numerous gaps in research regarding human-machine interaction and the introduction of generative AI tools, which should be filled in order to make meaningful use of them.

6. Conclusion

The aim of this paper is to analyse the opportunities and risks of generative AI tools from the perspective of employees in everyday working life in Germany. Challenges of human-machine interaction, especially bias, hallucinations, data protection, shifts in competence and cognitive stress. Based on this, the research question formulated at the beginning of the paper is answered: how does the use of ChatGPT or Copilot, for example, affect the German working world and what are the consequences for acceptance, efficiency and work processes? A systematic and critical analysis of empirical and theoretical works from Germany and comparable areas across Europe provides an overall picture of generative AI in the workplace. The focus is consistently on the employee perspective, thus filling a research gap by taking into account the technological, psychological and social aspects generative AI .

The results show that generative AI offers an opportunity to increase efficiency and make work easier, with the focus on automating routine tasks, supporting text and data processing, and promoting creativity. Employees are given new scope for action by making repetitive tasks easier. However, research shows that this cannot be achieved without risks and challenges. One problem is the lack of reliability of AI outputs, as bias and hallucinations occur frequently. As a result, the outputs of AI applications must always be checked by humans. Empirical evidence shows that AI results are rarely used to their full extent. The number of tasks that employees have to check is increasing, which leads to considerable cognitive strain. The tendency towards task fragmentation, the increase in multitasking and increased checking activities reduce job satisfaction and motivation. As a result, the increase in work efficiency promised by generative AI can only be realised to a limited extent. The lack of a governance framework in companies and the use of unauthorised generative AI tools also increase the risk of data misuse, which calls into question the acceptance of the technology by colleagues. The study shows that awareness measures, technical protection mechanisms and the participatory design of governance mechanisms are essential prerequisites for the safe and responsible use of generative AI.

Another challenge is the observed shift in skills. AI is changing the

skills required of employees, with routine tasks and repetitive work processes falling victim to automation through generative AI. New skills in the areas of meta-competence, problem solving, critical thinking, validation and evaluation are needed. Upskilling and reskilling are essential in order to adapt employees' skills to the new requirements created by the AI transformation and to secure long-term strategic advantages. Studies show that inexperienced workers in particular benefit from further training. There is a risk of de-skilling, which requires the continuous growth of employees' technological, analytical and regulatory skills. It is clear that skills development must be an ongoing process with diverse forms and content, as employees' learning requirements are shaped by their different experiences and tasks, as well as the varying extent of change in skills.
The ongoing adaptive design of training courses, whose content and timing are adapted to changing needs, is crucial for the most effective use of generative AI. Furthermore, the use of human-in-the-loop and adaptive feedback has proven effective in minimising wrong decisions and employee overload due to excessive workloads.

Empirical studies also show that the successful use of generative AI goes hand in hand with the existence of central governance structures and participatory co-determination. Units within companies that establish processes and responsibilities are much more successful in accepting generative AI and are more resilient to data protection violations. In addition, research shows a correlation between cooperation in multidisciplinary teams, employee participation in decision-making, and the existence of clear responsibilities. This correlation has an impact on the extent of psychological stress to which employees are exposed.

The paper finds that industry differences in the degree of automation, complexity and regulatory requirements have a significant impact on governance and training requirements .
In theory, the paper underpins the explanatory and predictive power of the job demands-resources model and skill-biased technological change. However, it expands on these with a focus on generative AI. The ambiguity of efficiency gains versus cognitive strain on employees and the development of governance structures, co-determination and participatory approaches are important issues that represent an essential construct in acceptance models and have not been considered to date.
By analysing the categories of compliance, data protection and co-determination separately

be introduced, the work contributes to the further development of classic acceptance models for the challenges of the AI age. The work will thus contribute to research. It brings together the previously separate theoretical and practice-oriented strands of research literature on human-machine interaction in the workplace and highlights new opportunities, risks and challenges associated with change in the field of lifelong learning and participatory leadership.

The work also highlights its limitations, as it focuses exclusively on secondary literature. Its limited generalisability also stems from the fact that the literature is restricted to Germany and Europe. Furthermore, the work does not contain any empirical data from its activities that could provide insights into individual stressors, motivational factors and industry-specific influences . .

The various studies and their comparability using different methods may lead to distortions in the weighting of results.

Further research is needed to demonstrate the effects of skill shifts on long-term employability, psychological stress and the benefits of various forms of participatory co-determination. In order to determine the extent of stress and describe industry-specific differences, it would be interesting to conduct a meta-analysis based on qualitative studies. Another direction that research could take would be to quantify skills acquisition in AI-related training using qualitative pre- and post-surveys. It would also be interesting to examine the impact of new regulatory requirements, such as the European AI Regulation, on the acceptance of generative AI among users and providers . . Working on this thesis has increased my understanding of the complex relationships between technology, organisation and people in the digital world. Examining different theories, empirical evidence and practice-oriented solutions and approaches has increased my understanding of the difficulties of integrating technology into work and the opportunities this presents. It has given me the ability to view a scientific question with sufficient distance and to present it critically and precisely. Furthermore, the analysis also highlighted the importance of analysis, reflection and critical questioning of scientific problems.

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Affidavit

I hereby declare that I have written this thesis independently and without the help of others. I have only used the sources and aids indicated and have identified any passages taken verbatim or in substance from these sources as such. This thesis has not been submitted to any other examination authority in identical or similar form.
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