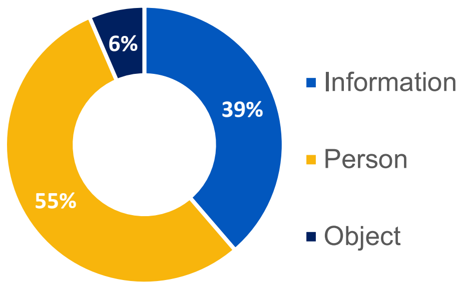
AUTOMATING COGNITIVE TASKS IN THE WORKPLACE USING AI-BASED SYSTEMS: CASES AND RECOMMENDATIONS

AI-based systems in the workplace

AI-based systems are slowly being integrated into more and more workplaces. A review of previous literature indicates that AI-based systems for the automation of cognitive tasks will primarily be used to perform **information-related** or **person-related tasks**[1] (Figure 1). Examples given in the literature are intelligent tutoring systems[2,3] to automate specific teaching tasks as a person-related task, or data collection and processing[4] as an information-related task.

Figure 1: Distribution of automated cognitive tasks by AI-based systems based on literature review



When consulting current literature, the potential for automation of a wide variety of cognitive tasks becomes apparent. There are potential applications in marketing, finance, education, customer support and many more.[5] These are mostly non-embodied AI-based systems. However, in some cases, an AI-based system can be combined with a physical presence to successfully perform a cognitive task. One example would be a service robot that functions as a social companion and automates minor cognitive tasks for their user.[6] But these represent systems that are currently being developed. For AI-based systems automating cognitive tasks, which are already actively being used by companies, a different focus emerges. Looking at the available landscape of case studies, it is noticeable that they do not match the distribution present in current literature. Current case studies **predominantly show information-related tasks as being automated**. Neither the literature review nor the accumulated case studies are a complete representation of current AI-based systems in the field and in development. This discrepancy is also rooted in the nature of scientific publications, which present research on a technology and its possible impacts before it becomes widespread in the market. The fact that the studied systems are still in the early stages of development and not yet robust enough is also addressed in some publications.[7]

However, this indicates that **in the future, more AI-based systems will be used to automate a variety of cognitive tasks**. As these systems continue to mature, one can already learn valuable lessons for the successful implementation based on use cases and case studies of companies that have successfully implemented them already.

As part of EU-OSHA's research on advanced robotic and AI-based systems for the automation of tasks and occupational safety and health (OSH), 11 case studies and 5 short case studies were developed that focus on workplaces that use these technologies. The following section presents three of them in an abstract way, in

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[1] EU-OSHA – European Agency for Safety and Health at Work, *Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and Occupational Safety and Health*, 2022. Available at: https://doi.org/10.2802/681779

[2] Sottilare, R., & Salas, E. (2018). Examining challenges and approaches to building intelligent tutoring systems for teams. In J. Johnston, R. Sottilare, A. M. Sinatra, & C. S. Burke (Eds), *Building intelligent tutoring systems for teams: Volume 19* (pp. 1-16). Emerald Publishing Limited. https://doi.org/10.1108/S1534-085620180000019001

[3] du Boulay, B., & Luckin, R. (2016). Modelling human teaching tactics and strategies for tutoring systems: 14 Years on. *International Journal Artificial Intelligence in Education, 26*, 393-404. https://doi.org/10.1007/s40593-015-0053-0

[4] Rheu, M., Youn Shin, J., Peng, W., & Huh-Yoo, J. (2020). Systematic review: Trust-building factors and implications for conversational agent design. *International Journal of Human–Computer Interaction, 37*(1), 81-96. https://doi.org/10.1080/10447318.2020.1807710

[5] EU-OSHA – European Agency for Safety and Health at Work, *Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and Occupational Safety and Health*, 2022. Available at: https://doi.org/10.2802/681779

[6] Góngora Alonso, S., Hamrioui, S., de la Torre Díez, I., Motta Cruz, E., López-Coronado, M., & Franco, M. (2019). Social robots for people with aging and dementia: A systematic review of literature. *Telemedicine and e-Health, 25*(7), 533-540. https://doi.org/10.1089/tmj.2018.0051

[7] Milne-Ives, M., de Cock, C., Lim, E., Harper Shehadeh, M., de Pennington, N., Mole, G., Normando, E., & Meinert, E. (2020). The effectiveness of artificial intelligence conversational agents in health care: Systematic review. *Journal of Medical Internet Research, 22*(10), Article e20346. https://doi.org/10.2196/20346

companies of varying sizes and degrees of automation within their company across Europe. Each of them automate a different cognitive task using an AI-based system.

Case Studies

Case 1

The Norwegian gas infrastructure company in this case study currently has over 350 employees and has multiple large worksites needing supervision and maintenance. Keeping these areas free of obstacles (for example, natural hazards, material detrition and man-made obstacles) is vital to keep areas safe to work in. However, as the worksites are large, and some areas require workers to perform dangerous tasks (for example, inspecting high construction), the company started to equip **drones** with modern camera technology and an **AI algorithm**. These drone-based visual inspection systems can safely be employed on site by an operator and fly to inspect an area for obstacles or hazards. The algorithm analyses the visual input for fallen or forgotten objects or work parts. It was **trained** on a large, **indexed, image database created by the company** to differentiate between, for example, tools forgotten by workers and other natural hazards or obstructions, like leaves. When the algorithm categorises an object as an obstacle that needs to be removed, the **operator is informed** and a worker is deployed to carry out the necessary follow-up tasks. The drones **do not replace thorough and detailed inspections** of machinery and parts, but they reduce the time spent on general retrieval and inspection in the field.

Interestingly, the company reported **no barriers** during the introduction of the system. One reason can potentially be found in the fact that the tasks that are automated can be described as being in the **'3Ds' ('dull, dirty and dangerous').**[8] These types of tasks are especially well suited for automation. Furthermore, the task of identifying a forgotten tool does not require a person to have any specialised skill; neither is it the primary task of any worker. The AI-based drone still needs to be operated by a worker, however, the overall time spent on performing this task is significantly reduced. Automating tasks that workers do not enjoy, while simultaneously allowing them to increase the time spent to focus on their primary tasks, might contribute to the high acceptance of the system. Likewise, **as it is not a core task of any worker, fear of job loss is potentially lower**.

The topic of **surveillance** is frequently brought up when talking about visual inspection through AI-based systems. Drones with cameras can be used for targeted visual inspections instead of classic worksite camera systems, avoiding unnecessary recordings of workers. This way, the drones allow **greater data privacy** for workers. This case study is of special interest as the AI implemented in the drones mainly affects **physical OSH**, while it automates a **primarily information-related cognitive task**.

Case 2

The non-profit organisation working in journalism and politics in England has under 50 employees. Their primary task is fact-checking statements made by influential social figures, politicians and companies, and correcting them, should they be false. For this, skilled journalists have to assess individual statements for falsehoods. This is a time- and resource-consuming process, as it involves active research into the claimed topics and extensive contextualisation. To reduce workload, this organisation developed an AI-based system capable of preselecting claims and statements with a high likelihood of being incorrect. The journalists then fact-check these flagged statements. The non-profit organisation used the Bidirectional Encoder Representations from Transformers (BERT) model. This is **a transformer-based machine learning technique for natural language processing (NLP)**. The non-profit organisation fine-tuned this model with their own annotated data.

This is an **AI-based** system automating an **information-related cognitive task**. This case study is a representation of what could be considered a 'traditional' application of an AI-based system. The system does not have a physical representation and, once operating, **integrates fully into a person's workflow**, to the point that an outside user might not be aware of the AI-based system at all. However, as the organisation developed the system themselves, their workers are aware of the technology. Nonetheless, this AI-based application does not fundamentally change the core task the journalists were performing. It rather reduces the time they previously spent on identifying if a claim needs further investigation or not. Researching the claim and providing accurate counter information, however, is still performed by the journalists, and more so than before. The system **assists them in their core task rather than substituting their expertise**.

It is important to inform workers if an AI-based system is recording data. However, it is equally important to inform them when it is not.

[8] Lin, P., Abney, K., & Bekey, G. A. (Eds) (2014). *Robot ethics: The ethical and social implications of robotics*. MIT Press.

Case 3

The third company is a conglomerate focusing on a variety of sectors like automation and digitalisation in the industry, infrastructure for buildings and decentralised energy systems. Today, it can be classified as an international company with branches in 190 countries, however, it was founded in 1947 in Germany.

The company uses an AI-based **computer vision system for product inspection**. The AI is part of an automated optical test method using **X-ray inspection** for working parts that are not easily accessible for visual inspection. An X-ray camera and a computer run a system that records and evaluates several tests on **soldering points in a workpiece**. Based on the X-ray images and previous data, the computer vision system **calculates whether a detected error is an actual error or a false positive**. If the algorithm determines a high likelihood for an error, the workpiece is then moved to individual testing, performed by a trained worker. By reducing false positives, the worker is **relieved of this unnecessary workload**. The AI-based system performs an **object-related cognitive task** and there is **no physical** manipulation of the workpiece. The company developed and trained this system themselves on an indexed database. Hence, this is a highly specialised AI-based system, which cannot easily be transferred to other users.

Workers receive notifications from the system if a workpiece needs further inspection. They then manually perform this inspection. The task of quality control was already automated to a certain degree, however, without the AI-based system. The **AI increases the accuracy and lowers the number of false positives** that enter inspection. This reduces workload and increases workers' control over their working time without having to consider backlog as much as before. As in the previous case studies, the **AI system does not substitute the workers' main task but rather enables them to perform it under better conditions**.

While the company has had reports of general fears of job loss in the context of process automation, there were no specific complaints linked to the introduction of AI-based systems. A reason could be that the step was already partially automated, and the AI-based system only improved upon that.

Recommendations

When integrating AI-based systems in the workplace, several factors can contribute to the success or failure of the implementation. Many AI-based solutions are often custom-fit to the specific task and environment in which they perform. Companies looking to automate a task using an AI-based system should first assess the suitability of said task to be automated and the system they intend to use. While some researchers suggest that AI developers should look for ways to 'solve volatile, uncertain, complex, and ambiguous challenges'[9] through the technology, current applications are moving in a different direction. In most case studies, a specifically trained algorithm provides as accurate results as possible. The case studies are **limited in their domain of knowledge and trained on specialised indexed data**. Once trained, transferring that AI-based system to a different field would be ineffective. While some address ambiguous challenges (for example, assessing the chance for a false positive), the systems perform best in non-volatile environments with limited parameters and complexity. They perform well in these domains and can benefit workers and OSH. Something that the provided cases have in common is the fact that the companies trained their systems by their own, or provided the data on which the integrator trained the system. One potential challenge with training any AI-based system can be found in the overrepresentation or underrepresentation of specific cases within the training data, which creates biased conclusions. **By creating and training on their own indexed data, companies have more control and can assess the data for bias.** This, however, does not necessarily fully protect workers from unconscious bias. The potential consequences of biased training data can be severe, especially if an AI-based system is involved in processes affecting a person's wellbeing (for example, medical decision support systems) or personal development (for example, human resources). In manufacturing, machine bias seems to primarily reduce efficiency. Nonetheless, any company considering the implementation of an AI-based system should either invest in **checking their own training data for bias or, if the system is bought from a third party, inquire about a way to prevent bias in their training data**.

Questions regarding **workers' attitudes towards AI-based systems** need to be asked in order to facilitate a successful introduction and long-term working conditions. The fear of job loss has been acknowledged as present due to continuous automation, however, how to successfully mitigate this fear specifically for AI-based systems proves difficult to find in current literature. Within the present case studies, companies have faced the fear of job loss within respective companies and handled it in different ways. Noticeably, AI-based systems without a physical representation seem to trigger this fear less intensely than those that are being used in combination with, for example, a robotic arm. One possible explanation for this is that these AI-based systems have changed the working environment to a lesser extent than more traditional physical automation. Most workers who interact with these systems benefit from them in terms of a reduced workload, while their previous

[9] Laplante, P., Milojicic, D., Serebryakov, S., & Bennett, D. (2020). Artificial intelligence and critical systems: From hype to reality. *Computer, 53*(11), 45-52. https://doi.org/10.1109/MC.2020.3006177

core task remains largely unchanged. To address concerns among workers, like fear of job loss, or ethical concerns about the technology, companies that report success in dealing with them have taken the approach of **comprehensive education**. This means that they provide workers, in some cases proactively, with information about the technology, beyond the training needed to operate it. In some cases, this information is also accessible for workers who at that time are not using the technology. This additional information focuses on the advantages the system brings to workers, how jobs are changing, and reassuring the workers that the aim of this automation is not to eliminate jobs. In addition, **companies that successfully deal with concerns or resistance during the implementation process tend to have good social support within their companies**. This can take the form of social counselling and anonymous feedback systems as well as contact personnel for any arising questions.

3D tasks are often described as having high potential to be automated. When looking into which tasks to automate, it can also be useful to not only focus on these types of tasks but also on secondary tasks. Secondary tasks would be anything that is not a primary component of any job, but rather has to be performed by workers on the side. The system presented in the first case study is checking for forgotten tools. Performing these tasks alongside of their main task might lead to disruptions in their actual workflow. When looking for potential areas to implement an AI-based system to automate 3D tasks, companies should invest time in identifying tasks that are automatable and can potentially decrease disruptions in the workers' routines and do not make up their primary task. While research in this area is needed, **automating secondary tasks might potentially be met with greater acceptance and might reduce negative psychosocial reactions among workers, like fear of job loss**.

It has to be highlighted that all companies are acutely aware of **the complex issue relating AI-based systems and data privacy**. **None of the described systems record, save or analyse any person-related data. This is by intentional design.** The systems are limited to very specific tasks, and predominantly do not come into contact with any person-related data. In the case of the gas infrastructure company, their drone technology can potentially visually 'ignore' person-related data of workers. The footage is not recorded or used to continuously train the AI-based system. And as the drone can be used for spot inspections, it provides workers with greater privacy than a traditional full-camera system at their worksite. **While loss of privacy is a highly important topic, it should not be used synonymously with AI-based systems to avoid creating negative bias towards AI applications as a whole.** The European Parliamentary Research Service, Scientific Foresight Unit report[10] recommends the full inclusion of workers and managers in all technology implementation. It contains the recommendation that data protection officers (DPOs) should not only include trade unions but also employer associations. For workers' rights protections, DPOs should, as recommended in the new European Commission AI Act, write codes of conduct to accompany any system processing sensitive data. In the context of involving affected parties in the implementation process, **companies should also communicate clearly and comprehensively the type of data the system is processing, whether it is recording any data and especially person-related data, and why any potential recordings are necessary or unavoidable, before implementing an AI-based system**. This should especially not be neglected if the system is not recording any data, to avoid uncertainty and the projection of negative presumptions by the users of the systems.

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[10] European Parliamentary Research Service. (2020). *Data subjects, digital surveillance, AI and the future of work*. https://doi.org/10.2861/879078