

Generative artificial intelligence adoption and employees' perspectives on AI at work: toward unalienated working life or AI-augmented alienation?

Visa Rantanen and Kathrin Komp-Leukkunen

Department of Social Sciences, School of Engineering Sciences, LUT University, Lappeenranta, Finland

Abstract

Purpose – Generative artificial intelligence (AI) is making its way into our working lives. Previous research has explored topics such as AI-related fears among working people and AI technology adoption in companies, but people's perceptions of AI in the context of AI adoption are still not well understood. This article looks at the intersection of AI technology adoption and AI-related job concerns in one company.

Design/methodology/approach – A rapid ethnographic case study of a Finnish energy company during its introduction of a generative AI tool was conducted. This article explores: (1) How is AI technology adoption managed? (2) How do employees perceive AI-related social risks concerning their working lives? And (3) how are perceived risks related to AI accommodated? We utilized Marx's framework on alienation to analyze employees' AI-related job concerns and future perceptions, and improvisational change management theory to analyze technology adoption strategy.

Findings – AI-related concerns included both job security-related and job quality-related concerns. AI-related fears also manifest in rhetorics on the alienation-reducing potential of AI and digital automation. Employees' initiative is emphasized in technology adoption, which underlines the importance of their AI acceptance.

Originality/value – The article illustrates how AI acceptance is constructed in work culture, and it also shows how a classic theory can be relevant for analyzing AI perceptions. It demonstrates why employees' AI acceptance is central in the context of employee-led practices in AI technology adoption.

Keywords Technology adoption, Ethnography, IT-enabled social innovation, Disruptive technology, Information workers, Organizational culture

Paper type Research article

1. Introduction

The history of capitalism is a history of growing productive forces (Marx, 1976; Acemoglu and Restrepo, 2018). Yet, industrial revolutions were also accompanied by technological unemployment and transformations in working conditions, for better or worse. These issues are currently being intensely debated again because of the far-reaching transformative digitalization stemming from artificial intelligence (AI). Researchers fear this technology may render skills outdated and trigger mass lay-offs (Xie *et al.*, 2021; Zhan *et al.*, 2024). Newspapers regularly feature articles that discuss how AI may take over jobs and make workers redundant (e.g. Marks, 2025; Subin, 2025). Recent surveys reflect the same concerns. They show that about every second US worker worries about future AI use at work, and about two out of three workers in Organization for Economic Co-operation and Development (OECD) countries worry about losing their jobs to AI in the coming years (Lane *et al.*, 2023; PEW Research Center, 2025).



Generative AI and digital process automation technologies offer automation potential to white-collar jobs. For blue-collar workers, AI represents a continuity of automation, starting from the first industrial revolution and continuing with computerization and robotization. However, for white-collar workers, it represents a sea change, bringing computerized automation to administrative tasks that were previously shielded from automation (Ribeiro *et al.*, 2021; Frey and Osborne, 2023). Automation may augment work, change task compositions or drive job changes, while creating a pervasive need for upskilling (Acemoglu and Restrepo, 2018). Concerns are growing, especially among those who are reluctant to retrain or are so young that they still have long working lives ahead of them (Innocenti and Golin, 2022; Zhan *et al.*, 2024).

Bielskis (2025) and Sidorkin (2025) reflect on these concerns, suggesting that they may give rise to job alienation through work displacement and work alteration, as described by Marx (1967). However, their suggestion has not yet been empirically studied to a wide extent. The present article fills this gap. It empirically studies how generative AI tools are introduced into a company, which allows for capturing the volatile and often ambiguous phase of technology introduction (Orlikowski and Hofman, 1997). This phase is especially rich in reflections and discourses on the effects of technology on working life, making it particularly suitable for the present study.

This study aims to develop a better understanding of this intersection of technological change in the workplace and employees' career-related risk profiling. This is done via a rapid ethnographic study of generative AI tool adoption among white-collar workers in a Finnish energy company. We approach our research aim by asking three interconnected research questions: (1) How is AI technology adoption managed as a change management process in the company? (2) How do employees perceive AI-related social risks concerning their working lives? (3) How are these perceived social risks related to AI accommodated at the company? The first research question seeks to describe the company's approach to adopting generative AI in order to understand the case context, and the two subsequent questions explore AI-related perceptions of social risks and their management as a workplace cultural issue – i.e. how AI-based technological change is rendered acceptable in the workplace. Our findings show that in white-collar work, information asymmetries between company personnel can create conditions that favor what Orlikowski and Hofman (1997) call an emergent change management strategy, which means that the introduction of AI technologies may empower employees in the early phase of technology adoption. Management highlighted automation's capacity to reduce alienation by eliminating repetitive tasks from administrative work. Employees repeated a similar rhetoric but with reservations, citing risks related to technological unemployment and loss of agency, the first two aspects of Marx's (1967) theory of alienation. We suggest that knowledge sharing and centering employee agency and job security may be beneficial for facilitating employee engagement with AI adoption.

2. Marx's theory of alienation as a conceptual lens for analyzing perspectives on AI

Marx (1967) proposes that humans have creative capacity in that they possess a mental representation of what they intend to create (species-being). Workers become estranged, in other words, alienated under capitalism in three ways. Firstly, alienation arises as they become dispossessed of the means and the products of labor. These two dispossessions are separate aspects of alienation in Marx's original formulation but are combined here for simplicity. Secondly, workers become alienated from the creative, self-driven aspect of work because the division of labor reduces work to simple repetitive actions within a wider production chain with no creative agency. This transformation of workers into automata is often understood as the root of alienation (Burns, 2024). Thirdly, workers become alienated from each other when they primarily interact with those who are unable to exercise their species being, thereby losing touch with the full aspect of humanity.

AI can remove workers from production via automation. This connects to the first aspect of alienation. The mathematical complexity of deep learning models goes beyond human comprehension, which is why AI can be regarded as a black box (More, 2023). Understanding the mechanics underlying the work process becomes impossible. Prompting or fixing the result of something that one does not understand reduces control and self-driven agency at work, potentially deepening the second aspect of alienation (Kabadayı, 2026). Küçükuncular and Ertugan (2026) suggest that AI-augmentation of work can reduce workers' perceived authorship of their work results. Furthermore, training deep learning algorithms requires repetitive classification tasks (Bielskis, 2024; More, 2023; Ruggiu and Özdemir, 2026). An increase of such tasks can escalate the second aspect of alienation and, as many of these jobs seem to be delegated to the Global South, could intensify global inequalities. Overreliance on AI may reduce workers' cognitive abilities, potentially reducing their capacity to perform creative and cognitively challenging tasks. Kabadayı (2026) calls this somatic alienation.

Regarding the third aspect of alienation, unemployment directly hinders social connections between workers. The threat of unemployment could also create technology resistance and conflicts at work (Valtonen and Holopainen, 2024). Zheng (2026) argues that much of this depends on how AI is implemented. Work disturbances and transparency issues related to job automation and AI adoption, such as AI washing, can create further distrust between employees, companies, and their stakeholders (Elhajjar and Itani, 2025).

However, AI's ability to replace social interaction and create anything truly new or free of AI hallucinations remains limited (Bielskis, 2024; More, 2023). AI might take over repetitive tasks, allowing workers to concentrate on deeper job aspects (Parycek *et al.*, 2024), which could reduce alienation. Sidorkin (2025) argues that the removal of arduous cognitive tasks could leave more time for human joy at work and, therefore, AI augmentation could allow humans to extend their creative capabilities in playful ways. Sidorkin calls this liberatory alienation. Zhang and Wang (2026) have argued that AI may also cause alienation for consumers. For instance, AI-driven recommendations in online services can limit user options and concentrate on options that are misaligned with what the user is looking for.

Marx mainly discusses alienation in connection with industrial manufacturing, where work consists of repetitive tasks in a mechanized production process. Marx (2005) defines machines as mechanical systems that reduce human agency by defining the pace of work, and tools as objects that humans use in accordance with their own pace of work. Thereby, generative AI-based technologies are tools rather than machines, since workers initiate the prompts at their own discretion. However, when workers are required to work in response to the generative AI outputs, this technology can also take on the role of a machine. AI technologies could come to restructure how work is carried out by concentrating work on prompting and re-prompting AI to try to make this black box work in one's favor.

While Marx is best known for his analysis of blue-collar work, he also discusses white-collar work, such as marketing and management (Marx, 1978). For him, these professions facilitate production without being directly part of it, e.g. through communication or analyses. Their job tasks involve expertise and autonomy, which makes them less suitable for automation and therefore less alienating (Burns, 2024). White-collar workers also often work in jobs where they manage information flows and have situational knowledge that needs to be comprehended to automate their work tasks (Kristal, 2020).

However, generative AI is the first technology that can take over some white-collar work tasks. It can generate content of human-made quality, for example in response to customer queries or administrative cases (Parycek *et al.*, 2024). Thereby, it introduces white-collar workers to debates about technology-induced productivity gains and possible redundancies (Acemoglu and Restrepo, 2018). We would expect that white-collar employees' perspectives on AI depend on what changes they foresee to their work tasks, working conditions, and career trajectories (Mei *et al.*, 2025; Zhan *et al.*, 2024). Additionally, employees may have concerns about how AI will shape the work community, such as the social relationships between employees (Mirbabaie *et al.*, 2022).

The application of Marx's theory to generative AI can be considered an analysis of a sociotechnical system, consisting of interactions between humans and technology within the organizational framework of the workplace. While this interaction is to be optimized for productivity outcomes, it may also interfere with social relationships and realities (Kudina and Van de Poel, 2024). Changing interactions with technology can affect job motivation, as outlined in the job characteristics model (Hackman and Oldham, 1980; Lu *et al.*, 2025). In light of this model, AI use at work may particularly interfere with the variety of skills required for the job, the need for workers to complete workpieces and the autonomy workers have. Since the uses of generative AI are diverse, its effects on these job characteristics will likewise be diverse.

Change management theorists such as Orlikowski and Hofman (1997) have long maintained that the advantages gained from software technologies are uncertain. Expectations and reality frequently differ. While companies sometimes adopt an anticipatory strategy, which plans for specific strategic advantages, these advantages may in fact be emergent and manifest only through experience. Sometimes companies adopt an emergent strategy, investing in a technology while expecting that specific uses will be discovered through experimenting with it. Companies can harness these through an opportunistic strategy, whereby identified uses are strengthened through additional investments or modifications to existing resources. Prior research suggests that Industry 4.0 technologies only yield productivity gains after several years, which suggests that there is a learning-by-doing effect (Cette *et al.*, 2022; Venturini, 2022). The two latter strategies imply that companies can be dependent on the initiative and feedback of ground-level employees to identify how technologies can be most useful.

Orlikowski (2000) argues that the relationship between technological and organizational change is dialectical, especially in the case of IT technologies. Here, both technology and the work organization need to adapt to one another. Organizational practices, culture and work processes need to evolve in response to technological development, but technological hiccups and experiences also help to further develop the technology. Fischer (1999), Adler (2015) and Stevens (2009) note that technology adoption frequently requires harmonization of stakeholder needs and behaviors via mutual learning between company departments, management and service providers, for example. This learning process constitutes an increased socialization of work (i.e. the interconnection between actors) in the Marxist sense (Stevens, 2009; Adler, 2015).

Stevens (2009) argues that this socialization has emancipatory potential, as it can harmonize sociotechnical systems with a broader set of human (stakeholder) needs. We agree, but add that, with automation technologies, the issue of alienation needs to be given special consideration. Marx saw the drive for increased relative surplus value as the core imperative in capitalism that drives technological development, i.e. automation, but it also undermines workers' interests. The profit motive is the one stakeholder interest that overrides others. However, if technology adoption involves workers' active participation, their stakeholder interests must be considered. We approach this issue by studying workers' acceptance of AI tools from the point of view of future-related perceptions and current user experiences to acknowledge the rapidly ongoing technological change.

3. Background on the company and its AI adoption process

A rapid ethnographic case study was conducted in a Finnish energy company. This company is internationally active in several sectors of the energy market and has hundreds of employees. It supplies private and corporate customers with energy commodities, such as gas, and also other types of energy sources, such as renewables. In recent years, the company has experienced significant growth in its economic scale, personnel and geographical reach. This study deals with generative AI adoption in the office environment of the company headquarters and, therefore, is not a case study on the energy sector as such. The company

presents a case of generative AI adoption in the context of white-collar work in large companies operating in complex business ecosystems.

When we first contacted the company, it had already acquired its own generative AI and started to introduce it to its employees. This in-house AI tool was a version of ChatGPT. Some employees had already used ChatGPT via OpenAI's ChatGPT website. The in-house tool was adopted to provide a more data-secure option for employees and to have an AI tool with access to the company's internal data. During the fieldwork, in the early fall of 2023, the company had begun a roll-out of this in-house AI tool, which involved training select employees on the basics of AI, giving them access to the tool, and later collecting feedback. While AI adoption was still in its early days, the company's IT department had pursued digital process automation of office work quite intensively over the previous three years.

4. Data and method

To conduct the study, the research team first came to an agreement with the company. This agreement gave the research team access to the company site and interviewees, and stipulated how data security, ethical, and privacy aspects beyond the General Data Protection Regulation had to be considered. After this agreement, a rapid ethnography was conducted over 3 weeks at the premises of the company's headquarters in the fall of 2023.

Ethnographic research collects information on cultures and habits (Vindrola-Padros, 2021). For this study, it was used to collect information on habits surrounding the use of generative AI and the culture that emerges around its use. Rapid ethnographies are ethnographic studies that are carried out over a shorter period because the researchers have limited access to the research site. This feature makes them suitable for studying organizations (Kumpunen and Vindrola-Padros, 2022). Ethnographies are also suitable for studying change processes within organizations (Campbell, 1998). Rapid ethnographies rely mainly on information collected through interviews and observations (Vindrola-Padros, 2021).

The data collection was carried out by the primary researcher, who was allowed to interview company employees on the company premises as long as it did not hinder their work. Therefore, the interviews typically took place during coffee breaks, lunch breaks, or similar break-like situations intertwined with everyday work activities. The primary researcher identified himself as a researcher in all situations. The social position of the researcher in this context was that of an outsider, but as business-related visitors regularly visit these premises, the presence of an outsider was not necessarily seen as anything unusual. The interviews followed the style of ethnographic interviews; they were conversational in nature but framed by questions relevant to the study focus (Walford, 2007). The thematic protocol featured questions about the workers' ideas about and current knowledge of AI, AI use, AI-related fears and broader thoughts about transformative work digitalization and future expectations.

Although not everyone working at the office participated in the interviews, the sample of employees covers most departments. A total of 35 employees were interviewed: 19 women and 16 men. Appendix Table A1 provides more details on the sample. Most interviews were conducted one-on-one, but sometimes, as the interviews were conducted in the common areas of the office, others joined in the conversation in the middle of an interview. Three interviews were carried out with a pair of workers and two with a group of three. The interviews typically lasted between 20 and 60 min. They were recorded by taking notes. Three one-on-one interviews were specifically scheduled at the initiative of the interviewees. Two of these scheduled interviews were audio-recorded, as there was suitable time to present informed consent forms to comply with the standards of the Finnish National Board for Research Integrity.

The researcher participated in 13 business meetings as an observer. These meetings dealt with the adoption of generative AI or digital process automation, covering topics such as employee training, planning, and co-learning events related to generative AI, feedback on the company's AI tool, workshops and negotiations related to digital process automation, and

meetings with AI-related service providers. The fieldwork did not use a strict observation protocol, but the note-taking concentrated on meeting conversations that dealt with company strategy and practices related to AI and technology adoption, as well as open observations that seemed relevant to the research aim and the themes explored in the interviews. Observations in the meetings were recorded using handwritten notes. Access to company business meetings was negotiated through a gatekeeper who worked for the IT department. The criterion for selecting which meetings to attend was that they somehow involved AI and/or digital process automation.

Altogether, the data comprised 172 pages of notes and 35 pages of transcribed audio recordings. Company employees were notified in writing about the study's purpose, that it did not seek to evaluate their performance, and that their participation was voluntary and anonymous. This was done via a notice on the company's internal communication channel and again verbally before each interview to avoid desirability bias. In addition, the researcher was introduced in person to each company department located on the floor where most of the interviews were carried out. Verbal informed consent was also obtained from interviewees at the beginning of each interview when the interview was recorded with handwritten notes. Signed informed consent forms were collected from audio-recorded interviewees. This approach is in line with the recommendations of the [Finnish National Board on Research Integrity \(2019\)](#) and [Kuula \(2006\)](#). We did not seek review from an institutional review board, as the design of this study does not involve elements that the [Finnish National Board on Research Integrity \(2019\)](#) deems to require such review.

Our analytical strategy is reminiscent of the style of institutional ethnography, looking at workers' experiences in relation to management practices and rhetoric within institutions ([Campbell, 1998](#)), though we focus on interviews and interaction in meetings rather than organizational documents. Interview data was initially analyzed without pre-existing theory, seeking to classify experiences based on what the respondents report in their own words and develop categories (for instance, AI and agency, automation connected to risk of unemployment and automation connected to more social work tasks) through inductive coding. We sought to make sense of management practices based on interviews and triangulate our findings based on observations. After gaining an overview of the data, theories of change management and alienation were utilized to gain a conceptual tool through which we could use our findings to build on existing theoretical knowledge.

5. Results

5.1 Technological change management at the company and the role of the IT department

The IT department had a central role in AI adoption. They prepared the company's generative AI tool, sought ways to improve it and trained other employees to use it. It also pursued digital process automation at the company. They trained staff from other departments to identify which of their work tasks could be suitable for automation. In the employee training sessions, these were described as tasks that are "regularly repeated," took "a lot of time" and were "boring but mandatory." In this sense, the AI adoption process was built on a pre-existing model of interaction, whereby the IT department trained employees about automation, but identifying which tasks would be useful to automate was then delegated to the employees themselves. As such, the technology adoption was not a top-down process. To enhance compliance with automation efforts, the employees were encouraged to think about it as something beneficial; if the boring and repetitive aspects of their work are automated, they can concentrate on more useful tasks over which they retain expertise. A human resource (HR) manager explained this to employees during a staff training session in this way:

People often assume that we need automation to be more efficient but really the driving factor is the employee experience—the wow factor—when everything just works smoothly. So, we need to think where we can raise the bar to get that wow factor.

In this pitch, automation was portrayed as a tool for employees to use to improve their own working conditions. An IT department employee described their role as “snooping around for surplus value” when describing what they sought from the new software technologies. The surplus value that the company was looking for was an increase in efficiency that could increase profits. They anticipated a specific benefit from automation, while realizing it was delegated to other employees. While there was a clear overarching goal, the practical application of the technology was located through an emergent strategy. The IT department’s role was not merely to provide tech support: rather, it was essential in managing technology adoption. This situation was also visible in the structure of the company headquarters. The company headquarters occupied two floors, and nonmanagement staff had been moved to the larger lower floor, which featured an open working space. However, the IT department had retained its place on the top floor, sharing the top of the pyramid with HRs and management.

Generative AI had not been adopted with an exact pre-existing goal in mind. Rather, the company wanted its employees to use AI “creatively.” As the IT department employee in charge of the in-house AI tool put it: “It’s [AI] on the rise right now.” Thus, generative AI adoption was a case of pure emergent change management. They were hoping that an in-house generative AI would make workers more comfortable using AI at work and that they would then find interesting uses for it themselves. This AI tool roll-out was managed through a procedure whereby small groups of employees were trained on the basics of AI and then given access to the in-house AI tool. After a trial period, employees were invited to a further training and feedback session to assess how useful the tool had been and evaluate how to further develop the tool and employee interaction with it. The IT department had started the roll-out with those employees that it estimated would have the most use for it; for example, staff in the communications department. Below is an example of an exchange from one training and feedback session:

Senior communications employee: [The in-house AI tool] is overly polite.

Junior communications employee: And too formal.

IT department employee: You can adjust this by pre-prompting.

Junior communications employee: [Tell it to] be ruder?

IT department employee: [Tell it] OK, you are a rude customer service agent, and then it should act accordingly.

[...]

Junior communications employee: What should we do when it says something wrong?

IT department employee: You have to check.

Junior communications employee: It lies when you don’t ask for the source.

IT department employee: It does not know anything. [...] It’s good at predicting.

The IT department employee’s role was essentially to facilitate use by providing advice and helping people to understand what AI is, its potential and limits; in short, to increase AI literacy and to encourage employees to keep an open mind about it. The training and feedback interactions would also help the company to assess how useful having a generative AI tool really was and where it required further development. According to the IT department employee, the company did not particularly care if the workers used other AI tools besides the in-house tool; rather, it wanted to stimulate use by providing them with a shared tool that would have access to company data but could be used without compromising data security.

5.2 Employee's AI use patterns and perceived AI-related social risks concerning their working lives

The majority of employees at the company seemed to have some experience with using AI, but few described themselves as frequent users. Most workers who had used AI at work had used generative AI for some specific work task once or twice out of curiosity, exploring what benefits it could offer. In most cases, the generative AI in question was the freely available ChatGPT. A minority of workers had used the in-house AI tool. Some had experience implementing various AI or machine learning solutions in company processes. Nine were recorded as not having knowingly used AI, while one person's AI use history was left vague. Those who did not use AI generally did not report being averse to it, but had not gotten around to using it yet, as the technology was new. Those who used the in-house AI tool typically worked in public relations or communications, as they were the first group of workers to whom the in-house tool had been introduced. Three of the workers interviewed described themselves as frequent users who used generative AI for "pretty much everything" (young male employee) or at least described having repeatedly used AI in core work tasks.

These frequent users were aware of risks related to AI, like copyright issues and factual errors in AI-produced content, but they were confident in their own abilities as AI users. They did not see the black box issue as a problem as AI was typically used as a sparring partner for fresh ideas or as a writing partner for reporting very general information. The loss of authorship and overreliance on AI were not seen as problematic either, as these people saw themselves as fundamentally in control: "I am still the one who makes the decisions," stated one communications employee. An employee from the finance department described generative AI as convenient for searching for information, as it can provide simple results fast: "It's faster than Google [. . .]: if I tried to search using Google, it would take about 30–40 min [. . .] and then I would get lost down some sidetracks." He described using ChatGPT to look for generic information and the right business jargon, and for coming up with new ideas. While errors could be problematic, in his reasoning, they should not be overly feared, as errors provide opportunities for learning to work better with AI, increasing one's AI competence as an emerged benefit.

Attitudes toward AI were not universally positive and trusting. One employee, an experienced coder, described the error-proneness and black box problem of AI as the main issues for him. His main source of concern was not merely the errors, but the larger social problem related to using AI. Due to what he described as the "black box" nature of AI, users cannot be sure what kind of biases the AI might have and who is responsible for them. For him, this power imbalance was a societal problem rather than something that affected his work directly, but he also brought up a similar issue in relation to AI and coding: "Sometimes I have had to clean up code written by these cheap coders [more junior-level coders]. I would not want to clean up code created by AI." He expressed concern about AI changing his work role from a code writer to merely a code fixer, while also being aware that the biases and limitations of AI could be societally significant and not directly observable or governable by users. This case illustrates how seeing oneself as the decision-maker in working with generative AI is highly dependent on how one sees generative AI in terms of Marx's distinction between a tool and a machine. In this case, the employee was referring to how his work may come to be orchestrated by a machine, with AI creating output that he would have to fix in response. He would not be the true orchestrator of AI-created content, as in his view, the tendencies in-built within the black box could dominate the coding process.

One employee from customer support had taken training on ChatGPT but did not describe himself as much of an AI user at work. He worked with the customer service chat function and was worried that AI may eventually automate a lot of the tasks of customer support personnel: "Quite a lot of it [his work] involves copy-pasting ready-made answers [matching correct answers to customer queries]". The pattern-matching potential of AI in automating customer support work particularly concerned him, as much of customer support was already in text format via online chat. Therefore, case reports on support requests could create opportunities

for training AIs. Increased efficiency was expected, but it was also seen as a potential problem. He was searching for a way of getting ahead of this before it negatively impacted his employment situation and had signed up for the company's AI training. On his lunch break, he checked out social media on his cellphone. He had seen a picture from a lecture that his friend had seen. It showed a talk by an AI guru on a stage. "AI won't replace you but someone who knows about AI will," read the text behind the lecturer, as he showed the image to the researcher. Dealing with technological unemployment fears was part of learning about AI.

High-level professional and managerial employees mostly described AI positively. They described using AI fairly little and for generic tasks that did not require very much attention to detail: "I asked ChatGPT to explain the factors determining the price of gas, then explained that same information to a reporter and the reporter bought it just like that," explained one male sales manager. Generative AI was again seen as something that is good at tasks that require dealing with soft information: "I just use it [ChatGPT] to search for information that deals with very general basic economics stuff," said one female employee in a high-level managerial position. She stated that she was worried that AI may make her less intelligent over time if it did all the thinking for her, but was not worried about inaccurate information, as she said she only uses it for topics where she feels she can immediately recognize what is wrong and what is right.

Preparing PowerPoint presentations for business meetings was commonly mentioned as an example of where these generic information-compiling functions came in handy. An employee who worked with human rights-related information described the nature of the information she deals with as highly uncertain. Her job required a high level of skepticism regarding information sources and double-checking multiple sources in all cases, so she could relativize the accuracy problems of AI to the softness of information in general: "Information on human rights is always very uncertain and imprecise anyways." According to her, getting an overall idea about a topic from ChatGPT can be a useful starting point before searching for deeper information from other sources.

These high-level employees trusted their professional expertise, believing that they would not be misled by AI-generated errors. The imprecision of generative AI was also relativized versus the commonness of human error. Overall, these employees struggled to identify time savings and qualitative improvements through AI use. However, they felt that generative AI functioned as an easy starting point for more complex tasks. AI use was described as something done out of curiosity and due to a perceived need to stay on top of new technologies. These users were following the emergent technology adoption approach, trying to discover what benefits the technology could offer, but had yet to find very significant uses. They were not frequent users, though they saw AI in a similar way to the frequent users: A tool for crafting generic content on demand to save effort, and a chance to develop personal competencies for working with AI to prepare for a more AI-augmented future.

Virtually all interviewees saw AI as still being in development. As one female employee in communications said: "It [AI] currently operates with something like a high school student's intelligence, what will happen when it grows up? [. . .] What are we all going to do for work then, become bakers?" But most interviewees expected AI not to affect their work agency or job security in the short term. Effects on the work community, such as power relations between departments, were noted in relation to broader transformative digitalization. For example, one older employee working in sales stated: "Sales has become a support department for the IT department when it should be the other way around." Complexity of digital systems, like modern customer relationship management software, such as Salesforce, was described as a clear change to the past, which forced sales and marketing personnel to spend more time dealing with technical problems or learning how to use complex systems. Even Excel files with complex coding could pose challenges. Technical problems could also force workers to deal with the IT department from a position of being more reliant on technical assistance. Furthermore, in highly automated systems, wrong data inputs due to typos or misplaced commas could end up being copied and repeated, culminating in errors repeating themselves

without human employees initially noticing them. Therefore, the remaining data input tasks could demand more attention to detail. An older sales employee described an instance where a client had been overcharged due to a simple input error, which then required many employees to check through a massive backlog of data points for repeated errors. He described how he and his colleague had started checking each other's work before saving new inputs to the sales management system. While AI and automation were described as ways of eliminating boring and repetitive tasks, automation sometimes also produces new repetitive tasks.

5.3 Aspirations of more social working lives and accommodations of automation risks

The management and professional-level employees were generally not concerned that AI would make them redundant. Instead, they envisaged a more automated world of work where they could concentrate on more meaningful activities. Being a more human-centered and sensitive communicator at work was commonly mentioned as something that people would devote more time and effort to if the “grunt work” was reduced by automation. There would be more time to spend on meetings, planning, and communication between employees at the company. A male employee from sales and marketing put it this way:

You always have to stay on the crest of the wave [...] if my current tasks were taken over, then I could actually devote more time to communicating with my colleagues here at the company and actually visit gas stations now and then to see how the concepts are working out.

Some managerial personnel admitted that AI and digital process automation could make workers redundant or had already reduced demand for labor. This development was contrasted with the chance of bringing about a more creative and human-centered work environment “that cannot be automated,” as one female employee from investment management put it. A male IT manager speculated: “From the point of view of time-saving, we could release some of the workforce, then the workforce would maybe do that creative stuff rather than the AI.” Employees in management and leadership roles often expressed the notion that AI will increase efficiency and free up time for creative and social tasks, while acknowledging that it may also eliminate jobs. The IT manager pondered:

Maybe some people won't find sensible work to do in this organization and will leave. I'm not talking about my own team but rather, like, umm, the more “grunt-level” work—the people who actually use the system [the software systems being automated].

Many nonmanagerial workers also characterized the future of AI-transformed work as concentrating on social interaction and planning, the idea being that if the repetitive aspects of jobs could be automated, job roles would concentrate on humanistic and communicative aspects. One female member of the HR department put it thus: “Human connection cannot be automated.” Another worker from the HR department expected their tasks to shift from managing employee information to collecting information about work processes suitable for digital process automation: “We will create those processes then.” A general expectation was that new duties could involve planning how things are done in the company. However, nonmanagerial employees were sometimes skeptical about this narrative as it implied that they would acquire managerial tasks. A female customer support worker commented: “Planning and development and that; but then on the other hand, it may be that there won't be any work!” This aspirational narrative may buffer, but not eliminate, concerns about technological unemployment.

5.4 AI-augmented work: gaining a new tool or walking into the machine?

The employees' perspectives on AI were diverse. Most were not particularly worried about the automating potential of AI, as they saw it as merely speeding up or eliminating generic tasks. Those who regarded AI as a potential threat worried that it might devalue their existing skills by automating their core tasks. This did not necessarily turn them against AI but motivated

them to find ways to upskill. Some worried that AI could reduce agency, e.g. by shifting work tasks from authoring code to merely fixing code. These concerns link back to the question of whether AI is a machine or a tool in Marx’s logic. For employees who worry about automation and downgrading of work tasks, AI takes on the role of a machine. It shapes their working role from above. In contrast, those who are aspirational about AI view it as a tool that lets them maintain their agency (“I am still the one who makes the decisions”). The difference between both groups is connected to their framing: Individuals emphasizing machine-like qualities of AI consider social change at the macro-level over time, while those seeing it as a tool that they themselves control focus on what AI offers for them at work at the current moment. [Table 1](#) summarizes the aspirational perspective on AI and the two risk perspectives – technological unemployment and loss of control – in relation to the first two aspects of Marx’s theory of alienation.

The aspirational perspective features the promise of ameliorating or even perhaps overcoming the third aspect of alienation in a restructured working life filled with less alienating creative and social tasks. The third dimension of Marx’s theory of labor alienation was not present in the perceived risks but rather in this aspirational perspective where technological change is understood to reduce alienation, turning Marx’s schema on the relationship between automation and alienation upside down. None of the interviewees fitted into the top-left box.

6. Discussion and conclusion

The company’s approach to adopting generative AI can be categorized as emergent. Employees were trained on AI and encouraged to experiment with it and report their findings. This way, the company was increasing its employees’ AI competencies while delegating the initiative for technology adoption to them. This strategy may eventually become opportunistic, according to [Orlikowski and Hofman’s \(1997\)](#) terminology, but during the fieldwork, resources – the cost of having the AI tool and training employees – were deployed prior to identifying exact uses. This emergent approach reflects a pre-existing model of interaction between the IT department and other departments, as the sequence of training and initiative delegation also existed in the implementation of digital process automation. This practice highlights the IT department’s shift into a quasi-managerial role during transformative digitalization. The emergent approach can accommodate the specificities of white-collar work, as it assumes that the employee’s expertise and autonomy are needed to find successful applications for the technology.

Secondly, our research dealt with how employees perceived AI-related social risks in their working lives. Their perceptions were future-focused and included concerns about loss of agency and job loss, but also aspirations that work will become focused on higher-order planning and development tasks. This narrative turns [Marx’s \(1967\)](#) theory of alienation upside down by connecting automation to emancipation from alienation by reducing tasks

Table 1. Perspectives on AI and aspects of alienation

		Automation threat	
		Higher	Lower
Agency-loss threat	Higher		Black box perspective: Concern about losing agency to AI
	Lower	Job security concern: Wanting to learn about AI for job security	Aspirational perspective: AI creating a more human-centric and creative working life
Note(s): The table applies Marx’s (1967) theory of alienation to the employees’ perspectives on AI’s potential effects on working lives			
Source(s): Authors’ own work			

associated with the second and third aspects of alienation. This is in line with [Sidorkin's \(2025\)](#) theory of liberatory alienation, although the employees did not describe AI use itself as empowering or joyful. The aspirational rhetoric was repeated by workers in different job positions with minor social differences. Since management's tasks already relate to planning and social interaction, they could easily embrace this rhetoric. Nonmanagerial staff echoed the rhetoric but with some dissonance, as it implied changes to their working roles due to the potential elimination of core tasks. Some openly expressed technological unemployment- or loss-of-agency-related concerns. Their lay perspective reflects the concerns about AI and alienation previously identified by [Bielskis \(2024\)](#), [More \(2023\)](#), and [Küçükuncular and Ertugan \(2026\)](#). However, work quality-related concerns were more about loss of agency than increased repetitiveness. For instance, one manager worried about a possible loss of thinking skills, i.e. somatic alienation ([Kabadayi, 2026](#)).

Thirdly, we explored how the company accommodated AI concerns. AI training emphasized employees' agency in prompting and experimenting, making them active agents in helping the IT department tailor the tool to employee needs. In digital process automation training, the employee experience was rhetorically assigned to center stage. Moreover, the prevalent discourse on AI underlined how work will become more focused on higher-order tasks and social interaction. Interestingly, this rhetoric does not deny the risk of technological unemployment. Instead, it posits seductive new perks to make up for it.

The findings show that in the introduction phase, workers consider AI from the perspective of future potential, expectations, and discourses, rather than actual practices. Therefore, mechanisms like those described in the job characteristics model ([Hackman and Oldham, 1980](#)) cannot yet fully unfold. The initial phase of this process is particularly suitable for exploratory studies, while more structured approaches such as the work characteristics model are more suitable for later phases.

However, information asymmetries ([Kristal, 2020](#)) influence AI adoption in white-collar work, which sets white-collar workers qualitatively apart from blue-collar workers. Companies rely on feedback and the practical initiative of ground-level employees teasing out where and how AI can be most useful. This dependency makes technology adoption a cooperative effort that relies on emergent or opportunistic change management strategies ([Orlikowski and Hofman, 1997](#)) in the early phase. As a side-effect, technology adoption becomes increasingly socialized—driven by interdependent cooperation, feedback and mutual learning between company departments representing different types of expert knowledge, as [Fischer \(1999\)](#), [Adler \(2015\)](#) and [Stevens \(2009\)](#) have theorized. The technology adoption process can create an increased need for harmonization of interest between workers and the company.

The aspirational discourse about a nonalienated and human-centered working life can give technology adoption a triumphalist narrative, where the interests of workers and managers are united. But as worries about unemployment risks and loss of work agency loom in the background, these aspects of alienation have not been fully sublated. Management can use aspirational rhetorics to motivate workers to adopt AI ([Maravelias et al., 2012](#)), but it would need to sublate the separation from creative agency at work and the separation from the means of production through unemployment to fully convince them. Theories of increasingly socialized (interdependent) technological change ([Stevens, 2009](#); [Adler, 2015](#)) need to be deepened to acknowledge that cooperation between departments alone does not necessarily overcome the first two aspects of alienation, which could hinder technology adoption efforts. While this contradiction remains, management rhetoric explicitly connected digital process automation to improving how employees experience work. Explicitly connecting AI adoption and its use to job crafting – i.e. employee-driven modification of work content to improve work satisfaction – could help to reduce perceived alienation threat in AI adoption more effectively, and thus more comprehensively socialize the adoption process.

Harmonizing stakeholder interests is also linked to the topic of AI washing ([Elhajjar and Itani, 2025](#)). Research on AI washing should consider that exaggerated claims of AI use may

stem from AI being adopted exploratively and knowledge of real AI-use-levels being dispersed between departments. The phases of training, exploration and feedback in AI adoption facilitate the sharing of AI use awareness within companies. This has practical implications, as sharing successful and unsuccessful user experiences outside the company may help them combat investors' concerns of AI washing. This could increase investor confidence, albeit at the possible cost of benefiting competitors. Companies sharing the results of exploratory AI adoption may be able to boost investor confidence, showing that they remain at the cutting edge of development.

Previous research has suggested that cooperation and mutual learning between departments mitigates employee resistance to technological change (Valtonen and Holopainen, 2024). The adoption of Industry 4.0 technologies may favor practices where frontline employees are given a high level of agency. In addition, the mutual learning and long transitional periods that Industry 4.0 technologies require (Cette *et al.*, 2022; Venturini, 2022) may quench technological unemployment worries by facilitating employee reassignment (Zheng, 2026). Emphasizing employee agency-centered aspects of improvisational change management while promoting job security may also deepen worker participation in technology adoption. Future research should seek to test whether companies employing these strategies have an advantage in AI adoption and digital process automation.

The findings also have methodological implications, highlighting the relevance of Marx's (1967, 1978, 2005) theory of alienation for understanding perceptions of generative AI and digital automation technologies. This classic framework is suitable for analyzing the current introduction of workplace AI and may be useful in tracing how the use of workplace AI develops over time.

Finally, there are some limitations to consider. Our observations are limited to the early phase of technology adoption and, therefore, do not reflect long-term use persistence. In addition, the results are from a context where AI is still a relatively new technology and is assessed with future developments in mind. Employee perceptions about AI are likely to reflect a baseline that can evolve as this technology matures and user experiences accumulate. The interviewees were ensured anonymity, but interviewing employees at the site may still have contributed to desirability bias and the interview responses may contain artifacts related to social desirability. Data was collected on generative AI and digital process automation, but the company was not yet actively using AI-infused digital process automation. The impact of AI-infused digital process automation could lead to somewhat different results because it may identify tasks to automate without the employees' involvement. Finland is among the most strongly digitalized societies in Europe (European Commission, 2025). Countries with different work cultures progress through digitalization at different speeds; other cultures may be less conducive to horizontal practices in technology adoption and employee responses to digital change may vary by cultural context (Nissim and Simon, 2021). Further research will show whether geographical or cultural differences influence how generative AI affects work culture. As our case was a large company, its resources likely made it relatively well prepared to experiment with new technology. Emergent technology adoption may be less prevalent in firms with more limited resources. Further research is needed to assess the effect of company size on change management practices.

Automation is affecting white-collar work more fundamentally nowadays, which is influencing work culture. It seems that implementing automation technologies requires participation from white-collar workers themselves. This means that the interests of these workers need to be considered to achieve successful technology adoption. Achieving a high level of automation in white-collar work may require employers to also consider how to buffer employees' risk perceptions related to potential job losses or negative changes to agency at work. But the companies that can achieve this could be able to integrate AI and other automation technologies with their work processes at a deeper level.

Appendix

Table A1. Interview participant sample characteristics

Demographic categories	Subcategories	Frequency
Gender	Male	16
	Female	19
Job role	Communications or marketing	7
	Sales	2
	Customer services	5
	Supply and logistics	1
	Financial management	6
	IT	2
	HR	2
	Other	10
AI experience level	Frequent user	3
	Some experience	22
	Reported not having used AI	9
	Uncategorized*	1

Note(s): Five interviewees reported having managerial duties. Communications and marketing are shown combined to ensure effective anonymity of research participants. The group Other includes participants who worked with renewables or had highly specialized job roles separate from other categories

*One person was left uncategorized due to lack of detail in fieldnotes

Source(s): Authors' own work

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Corresponding author

Visa Rantanen can be contacted at: visa.rantanen@lut.fi

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