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Research Article

# Process industry disrupted: AI and the need for human orchestration

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ABSTRACT

According to EU policy makers, the introduction of AI within Process Industry will help big manufacturing companies to become more sustainable. At the same time, concerns arise about future work in these industries. As the EU also wants to actively pursue *human-centered* AI, this raises the question how to implement AI within Process Industry in a way that is sustainable and takes views and interests of workers in this sector into account. To provide an answer, we conducted 'ethics parallel research' which involves empirical research. We conducted an ethnographic study of AI development within process industry and specifically looked into the innovation process in two manufacturing plants. We showed subtle but important differences that come with the respective job related duties. While engineers continuously alter the plant as being a technical system; operators hold a rather symbiotic relationship with the production process on site. Building on the framework of different mechanisms of techno-moral change we highlight three ways in which workers might be morally impacted by AI. 1. Decisional - alongside the developmental of data analytic tools respective roles and duties are being decided; 2. Relational - Data analytic tools might exacerbate a power imbalance where engineers may re-script the work of operators; 3. Perceptual - Data analytic technologies mediate perceptions thus changing the relationship operators have to the production process. While in Industry 4.0 the problem is framed in terms of 'suboptimal use', in Industry 5.0 the problem should be thought of as 'suboptimal development'.

## Introduction

Artificial Intelligence (AI) in process manufacturing is thought of as one of the most important enablers of Industry 4.0. The so-called fourth revolution refers to a transformation in industry building on technologies that allow an automated and interconnected manufacturing process (Dregger et al., 2018; Molino et al., 2021). These changes in the manufacturing plant are about being equipped for using data-analytic tools to improve decision making. Technologies often mentioned in the context of Industry 4.0 are the internet of things, big data analytics, cloud computing, smart factories, artificial intelligence, and cyber-physical production systems(Dregger et al., 2018; Lemstra & de Mesquita, 2023; Molino et al., 2021; Thoben et al., 2017) . Along these lines AI applications are being developed for process industry (Winter & Peters, 2019). Industry 4.0 can be seen as primarily technologically-driven and focused on efficiency and flexibility (Ghobakhloo et al., 2023; Xu et al., 2021) Interestingly, 'industry 5.0′ is currently being developed to align such technological advancements with human-centered values (Breque et al., 2021). In 2020, the concept of Industry 5.0 was introduced during a workshop organized by the European Commission, where research and technology organizations and funding agencies discussed the future vision for industry (Müller, 2020). Industry 5.0 aims to reposition Industry 4.0 enabling technologies to become human-centric, sustainable-, and resilience-driven; '*the European Commission has designed a strategic path that, effectively executed, will transform traditional factories into resilient providers of prosperity, thereby evolving production centres into respectful components for environmental and societal well-being* '(Vyhmeister & Castane, 2024)

The route to I4.0 was initially being framed as a balancing act between what is technological feasible and labor-politically desirable (Dregger et al., 2018). At first a '*limited willingness to adopt new technologies and a company culture not ready for digitalization*' were considered important barriers to the use of AI (Winter & Peters, 2019). Emphasis in the industry 4.0 literature had been on safe human-robot interaction and accountability (Thoben et al., 2017) or highlighted the importance of providing training to all employees, in order to support Industry 4.0 transformations without impacting on workers' motivation (Molino et al., 2021). I5.0 in contrast to I4.0 centers around human

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needs and actually challenges the dominant paradigm of efficiency in I4.0. While 'human factors' have been discussed in I4.0 literature, it does this instrumentally and fails to address the psychosocial factors (Neumann et al., 2021). Three principal pillars distinguish Industry 5.0: 1) human-centeredness: a human-centric approach that emphasizes human needs in the centrality of production processes; 2) sustainability: engaging in initiatives such as recycling, waste reduction, and creation of circular processes to respect planetary boundaries, and 3) resilience: ensuring that industrial production is prepared against disruptions and is able to continue functioning in times of crises (Breque et al., 2021)

The co-existence of both I4.0 and I5.0 is telling for the societal challenges that are currently being navigated (Breque et al., 2021; Ghobakhloo et al., 2023). I5.0 seems to be an attempt to navigate the soft impact of AI in this industry; indirect consequences in terms of behaviors, practices, norms or routines (Swierstra & Te Molder, 2012). We argues this is a symptom of techno-moral change (Danaher & Sætra, 2023; Swierstra et al., 2009). What is more, as we acknowledge that workers in these industries and the way they relate to AI matter (i.e., I5.0), it becomes imperative to consider meaningful work in AI development and implementation. Indeed, critics of I4.0 argue that it has overlooked crucial human factors essential for designing systems that promote well-being, trust, motivation, and performance (Passalacqua et al., 2024; Sitarević et al., 2023). The authors highlight a significant gap between empirical and non-empirical studies and call for more experimental research on human-AI interaction in the framework of I5.0.

How to establish 'good' human-AI interactions? The current discourse on AI ethics focuses either on the artefact level, like ethics by design (Wang & Blok, 2025), or on broad, principle-based frameworks addressing values like fairness, privacy, and accountability; non-empirical ethics so to speak (Hagendorff, 2020; Jobin et al., 2019). These frameworks are often externally applied and do not necessarily reflect the lived realities of AI practice, nor consider social-political issues like power structures and ecological dependencies (Ryan et al., 2024), but rather reflect a contractual type of arguing (Crawford & Calo, 2016; Held, 1987). AI should be seen in the context of a socio-technical system that takes multiple levels into account, ranging from the artefact the socio-political and ontological considerations (Ryan et al., 2024; Stahl, 2022). In a recent study, empirical findings support the need to broaden the scope of ethics of AI to establish 'good' human-AI interactions (Ryan et al., 2024).

In this article, we aim to contribute to this debate concerning I5.0 by broadening our understanding of how AI might impact Process Industry in terms of human-AI interactions. We raise two research questions: First (RQ 1) - How do workers in Process Industry currently interact with their socio-technical surrounding? Second (RQ 2) - How would AI potentially affect these relationships? We start by introducing our overall approach; 'ethics parallel research' (Jongsma & Bredenoord, 2020). We continue to present our research along these categories. One important aspect being empirical research. To analyze our qualitative data we build on the framework of Danaher and Sætra whose taxonomy of different mechanisms of techno-moral change has allowed us to highlight three ways in which workers might be (morally) impacted by AI (Danaher & Sætra, 2023).

## Ethics parallel research

We depart from the idea that technology is not merely a neutral instrument (Gabriels, 2018). Rather, we make two general assumptions, namely that first, technology is value- laden and mediates our perception of reality, our behavior, and influences our norms and values (Blok, 2024). Second, technology is more than a collection of artefacts, as it also refers to the practices and processes around it and its embeddedness in social structures (Bijker et al., 1987; Gabriels, 2018; Murphie & Potts, 2017) .These assumptions inspired the emergence of the field of responsible innovation (RI), which argue for the identification of the ethical and societal aspects of technological innovations at an early stage by means of reflection and anticipation so that these can be taken into account in the innovation process (Owen et al., 2013; Popa et al., 2020). Jongsma & Bredenoord (2020) however introduce the term "ethics parallel research," to formalize concepts and tools of ethics research that researchers in this fields are increasingly adopting to proactively guide and evaluate innovations. We interpret these here as a way to operationalize these RI-principles. Ethics parallel research involves providing ethical guidance throughout the technology development process, rather than after its completion. This approach is pragmatic and constructive, aiming to both guide development and offer input for normative evaluation. Drawing from ethics and disciplines like Science and Technology Studies (STS), social sciences, and philosophy of technology, it seeks to address the ethical challenges of innovation effectively. Similar to Mclennan they advocate for ethicists working directly alongside technology developers to address ethical concerns in real-time (McLennan et al., 2020). Both approaches emphasize the importance of ethicists and philosophers being integrated into the development process to ensure that ethical and societal considerations are addressed continuously, not just as an afterthought.

In this paper we adopted an ethics parallel research approach to critically engage in human-AI interactions in the process industry. Over the course of two years we collaborated with the Institute for Sustainable Process Technology (ISPT), an NGO that promotes open innovation within process industry. The project was called 'the social acceptance of AI (SAAI)'. Together with the department of chemometrics at Radboud University and a big industry partner we collaborated in the development of a data-analytic AI tool. Our research can be discerned in to similar categories made by Bredenoord & Jongsma as it concerns (1) disentangling wicked problems (2) upstream or midstream ethical analysis, it is (3) ethics from within, it includes (4) empirical research, fosters future (5) participatory design and it focuses on (6) societal impacts (Jongsma & Bredenoord, 2020). Rather than traditional tools for research these categories offer a way to organize the different efforts ethicist put into doing responsible innovation.

## Disentangling wicked problems; job-enabling AI & meaningful work

Inherent to every problem definition is that the framing of the problem is also prescriptive in terms of stakeholders and responsibilities; calling an issue a 'wicked problem' acknowledges the difficulty to do exactly this (Brun & Betz, 2016; Jongsma & Bredenoord, 2020; Lönngren & Van Poeck, 2021). Here we attempt to unravel issues related to human-centered AI in this industry. I5.0 is going to help process industry become sustainable and make work more meaningful by means of human-robot collaboration, yet by definition 'soft impacts' of AI remain hidden. In 2021 a report concerning AI development written for Dutch Government calls for employees to be equipped with the right instruments and center development around its practice rather than the technology (WRR, 2021). To understand the outcome of this report we need to understand the background of this wicked issue. This need to start putting employees center-stage is grounded in a broader societal context as it ties in with two related arguments discussed in the AI literature.

1. That industry needs to govern innovations towards job-enabling AI and meaningful work (Acemoglu & Restrepo, 2019; Smids et al., 2020)
2. That industry needs to actively pursue skill-development (Acemoglu & Restrepo, 2019; Beane, 2019; Smids et al., 2020)

In terms of social justice, AI innovations have been criticized for not being able to pursue broad-based prosperity. Acemoglu & Restrepo argue that current thinking about AI, innovation and automation in terms of jobs is too optimistic (Acemoglu & Restrepo, 2019). The logic of current debates that by technological advancement productivity will go up like it did during an episode of agricultural mechanization is contradicted by more recent research. The authors point out a study on automation in manufacturing in the United States from 1990 to 2007 showed a population-wide loss of about three workers per robot and a 0.4% reduction in wages. The economists argue that appropriate governance is decisive. If innovation is left to the market sphere the risk of ending up with a 'wrong-kind' of AI is significant; AI replacing jobs while insufficiently increasing productivity to generate new jobs. This would merely increase automation and displacement and thus contribute to joblessness, anemic growth and inequality. It is shown that even when productivity is peaking over the past several decades, median wages have not risen (Galston, 2014). Additionally the skill-bias in technical change entails the phenomenon that a shift in production technology favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand (Autor et al., 2003; Parker et al., 2019). Berkers and colleagues showed in their research into the effects of automation and robotization in logistics that its mostly higher educated management that are able to seize the opportunities of smart innovations while lower educated employees have to deal with the threats of automation (Berkers et al., 2020).

Potential negative consequences of AI do not only concern social economic status but also concern work as being meaningful in terms of exercising skill and self-development (Smids et al., 2020). Beane and colleagues argue that AI 'pushes' trainees away from their "learning edge" (Beane, 2019). Opportunities for the development of job-related skill that were traditionally passed on through on-the-job learning, '*see one, do one, teach one*', such as training for medical procedures or investment banking, become limited. Experts are no longer doing hands-on work, and those who are being trained are expected to master both old and new methods, all while standard training methods are presumed to remain effective (Beane, 2019). The latter suggests that technology and skill are being treated as competing for resources, where skill lacks behind on technology. Paradoxically, while one might worry about job-enabling AI it should be noted that many factories have had trouble finding (and keeping) workers despite the pandemic pushing millions out of work in the US (newspaper article). Raising the question why?

Micheal Sandel argues in 'The Tyranny of Merit' that the former can be explained in terms of a need for recognition of work in production (Sandel, 2020). A lack of a sense of purpose constrains the improvement of these industries. What Sandel underscores is the importance of recognition for our share in terms of production, recognition for the work that is being done. Purpose is not merely translatable in terms of a paycheck, it is very much about the acknowledgement of the worker within his respective role. It is therefore not unsurprising that the concept of meaningful work has recently received increased attention in the context of robotization and AI and is especially valuable to process industry. Digital technologies may further obscure the role workers play as producers. Which applies, for example, to operators in process industry. Hence, meaningful work should be discussed in this context.

## Upstream or midstream ethical analysis

To navigate the so-called Collingridge dilemma, a dilemma between having enough control to alter the path of innovations versus having enough information to know which route to take, we aimed to put meaningful work on the agenda for ethical examination during the early stages of technological development (Kudina & Verbeek, 2019; Reijers et al., 2018). When we started our project late 2019 there were still very few AI technologies being developed while many data-driven tools had and have not found there ways into practice; making this an ex ante approach (Reijers et al., 2018). Together with the Institute for Sustainable Process Technology (ISPT) we reached out to several companies looking to discuss the implementation of AI. While in theory most parties seemed curious about the implications of AI, in practice there have been quite some hurdles.

We had developed relations with six eligible companies. All of which we provided with information about our project, we developed shared goals during meetings and who we developed recruitment material for. In four of these six companies management ultimately decided that our plans were too 'academic', deeming our 'soft impact' approach as having little relevance for their business cases; or too 'explorative', where there seemed to be little direct benefit of conducting interviews. In addition, most parties didn't have any AI yet en those who had developed new tools were not ready to open this up for scrutiny (yet). As Bredenoord & Jongsma argue, the success of this step relies heavily on the reflexivity and willingness of researchers to integrate perspectives and interests of 'outsiders' in 'their' technology. As such we depended heavily on the efforts of the chemometric department that allowed us to work with their affiliates

Eventually two of the six companies allowed us to conduct our research which make up two complementary situations. The chemical factory plant; *Pre- implementation*, and one a pharmaceutical factory plant; *Post-implementation*. Both factories concern the development and implementation of a data- analytic tool to support decision making within the work-routine. This has allowed us to investigate how workers in Process Industry currently interact within these factories (RQ1) and to theorize how AI could potentially affect these relationships (RQ2). Based on the prior argument, that to challenge the wicked problem of AI implementation for I5.0, practice is in need of the 'good kind of AI' (Acemoglu & Restrepo, 2019) and that technology development is biased against low-skilled workers, it makes sense to prioritize a definition of good AI development practice based on the experience of all employees in the workplace. More so studying innovations in the settings where they are developed makes sure implications can be better anticipated (McLennan et al., 2020).

## Ethics from within

### *Empirical research; ethnography*

We conducted ethnographic research departing from RQ1. How do workers in Process Industry currently interact with their socio-technical surrounding? And RQ2: How would AI potentially affect these relationships? As such we conducted participant observations and face-to-face in-depth interviews. We can distinguish three main aspects of our ethnography.

1. **Embedded in developmental practice** - from the start of the project a humanities scholar has been embedded both in the chemometric group of Radboud University where engineers would develop data-analytic tools; took part in project meetings with their industrial partners; and visit and take part in events organized by ISPT.
2. **Observations in the workplace** – While the Covid pandemic forced industry to close their doors for visitors from the outside, by means of videoconferencing operators of both factories made an effort to guide us through, and explain their work on-site.
3. **Interviews with Process Industry employees** – Both factories offered ample opportunity to conduct interviews. In the pharmaceutical factory plant we did purposive (criterion) sampling – we looked for participants who worked within the plant and were either end-users or developers of the newly developed technology. In the chemical factory plant we interviewed participants who worked within the plant; not depending on a specific type of technology we could do snowball sampling. Data saturation determined sample size.

Analyses in ethnographic studies yield different narrative findings most often a detailed description of a culture, or in this context a work environment, that reflect human experience (Murchison, 2010). In the context of ethics parallel research we have become re-scriptive in the sense that we have let ourselves become the narrator of several underlying normative tensions (Pols, 2015). Before we delve into the results we present the description of the two factories and their respective role-related duties.

**1. Chemical Plant – Before implementation**

The chemical factory produces large batches of chemical compounds and sells them to companies that manufacture everyday products. They are operating internationally. We studied the progress of a data-analytic tool in an early stage of development. Researchers trained their model using historical data from the factory plant, modelling different assets to be able to predict production outcomes. Its implications had to still be negotiated. We talked to 6 individuals directly related to the development of the tool, met with 3 individuals related to the company and interviewed another 6 employees regarding innovation within their work.

Summarized in the timeline below:

**2019 Fall**

- Two meetings with corporate senior innovator ($n = 1$)
- In-depth interview with corporate lead and expert in digitalization ($n = 1$)
- Project meeting corporate senior innovator and researchers/ tool-developers ($n = 3$)

**2020 Spring**

- Meeting between management factory plant en tool-developers ($n = 5$) Online
- Meeting between plant staff en tool-developers ($n = 8$) Online

**2020 Fall**

- Tour through the factory plant by an operator holding a tablet ($n = 1$) Online
- Observations; 3 regular meetings by plant staff ($n = 5$) Online
- Interviews with staff operators, engineers, managers ($n = 6$) Online

*Case 2 pharmaceutical plant – after implementation*

The pharmaceutical factory is a facility where the production of medications and pharmaceutical products takes place. This plant plays a crucial role in the development, manufacturing, and packaging of drugs that are distributed to healthcare providers and consumers. Many of the production processes contain living cells. At this site we studied the uptake of a data-analytic tool soon after implementation. Summarized in the timeline below:

**2020 spring**

- Two meetings were held with members of a data-analytic team ($n = 3$) Online

**Early 2021** Factory plan visit (1wk. online)

- Tour through the factory plant by an operator holding a tablet. ($n = 1$) Online
- Interviews with staff (operators, engineers, managers) ($n = 6$) Online

## Job descriptions

*Operator*

An operator in process industry is responsible for overseeing and controlling industrial processes to ensure safe, efficient, and high-quality production. Their tasks include monitoring equipment, adjusting process parameters and ensuring safety by responding to alarms and hazardous situations. Operators keep accurate records of operations, report issues, and collaborate with other teams like engineering and maintenance. Operators work in various industries, including chemical plants, oil and gas, and pharmaceuticals. This position typically requires an EQF level 3 or 4 qualification in technology and involves shift work, including weekends. The shifts are 07:00 to 15:00, 15:00 to 23:00, and 23:00 to 07:00.

*Engineer*

Depending on the level of education one can speak of either a technician or an engineer (EQF level 5 or 6). They differ in scope and responsibility but have similar tasks. A technician holds a technical diploma or associate degree in a relevant field, such as industrial technology or applied science. In this position you are considered a technical expert responsible for overseeing the operations and maintenance of industrial equipment and systems. They play a critical role in the maintenance, troubleshooting, and repair of machinery, ensuring the efficient and safe functioning of processes. Technicians also contribute to process optimization by identifying areas for improvement, implementing corrective actions, and recommending system upgrades. They work closely with engineers, operators, and other departments to resolve technical issues and improve overall performance.

A Process Engineer typically holds a bachelor degree in engineering and is responsible for designing, optimizing, and maintaining industrial processes to ensure efficiency, safety, and compliance with regulatory standards. They work with cross-functional teams to identify improvements. A key part of the role is monitoring process performance, troubleshooting issues, and implementing solutions to enhance productivity, reduce costs, and improve product quality. Process Engineers also play a significant role in scaling up lab processes to full production, ensuring proper equipment installation and operation, and supporting ongoing maintenance efforts. The role may also involve training operators and collaborating with R&D teams to implement new technologies.

*Relations on site*

The different types of employees relate differently to the factory plant because of their job orientations. While technicians and engineers preside over the production process as a technical system that need continuous improvement; operators are responsible for monitoring and controlling the day-to-day operation of the process, adjusting parameters, and ensuring production runs smoothly and safely. While technicians handle technical problems and equipment upkeep, operators manage the continuous flow and performance of the process itself. Managers on a production facility typically started out as engineer but now handle strategic planning and resource allocation, and thus prioritize overall performance, cost control, and compliance.

*In this table the job descriptions of the people we interviewed*

| Chemical Factory | | Pharmaceutical Factory | |
|---|---|---|---|
| Plant Manager | notes | Staff Manufacturing Process Specialist | notes |
| Process Technician | notes | Senior Operator & Trainingsspecialist | notes |
| Operator | notes | Operator | Audio |
| Continuous Improvement Manager | Audio | Senior Lead Data Analytics | Audio |
| Technician | Audio | Chemical Technician & Process Owner | Audio |
| Gatekeeper | Audio | Senior Manufacturing Data Analyst | Audio |
| Continuous Improvement Manager | Audio | Advanced Analytics Program Manager | Audio |
| Controller | Audio | Senior Proces Operator | Audio |

(*continued on next page*)

(*continued*)

| Chemical Factory | | Pharmaceutical Factory | |
|---|---|---|---|
| Continuous Improvement Manager | Audio | Manufacturing Supervisor | Audio |

Having so much qualitative data forced us to cut down on the material presented here, which is therefore not in any way exhaustive. We worked with private companies that did not allow to fully present the transcripts of our recorded visits and interviews. In addition to the recordings we used fieldnotes in which we paraphrase statements. We focus on those data that concern statements about employees relative position in the company and statements related to the dimensions of change and the changing nature of work with regard to new technologies and innovations.

We present our findings along the 'mechanisms of techno-moral change'. Danaher argues that technology affects moral beliefs in three domains; 1. Decisional 2. Relational and 3. Perceptual. He identifies six mechanisms related to these domains. The latter three help us describe techno-moral change within this industry (Danaher & Sætra, 2023).

(i) adding options;
(ii) changing decision-making costs
(iii) enabling new relationships;
(iv) **changing the burdens and expectations within relationships**
(v) **changing the balance of power in relationships; and**
(vi) **changing perception (information, mental models and metaphors)**

## Decisional

*Changing the burdens and expectations within relationships*

*Chemical plant*

In Spring 2020 we followed an early-career academic researcher who was in the process of developing a process analytical tool for the chemical factory plant. The researcher developed a 'path-model' that allowed him to program different 'blocks' that each represent a part or section of the factory plant. For example each block could mean a mixer or a heater or something else. Having dealt with the model 'in theory' it was time for what different stakeholders called 'secondments' where the chemometric researcher would visit the factory plant to experience in real life the meaning of the data he had been working with over the past three years. Because of the pandemic it was decided to have meetings discussing his tool online. It was this researchers' intention to invite employees with different organizational roles in order for different sorts of knowledge and experience to contribute in how to make sense of the tool. Present were a plant manager, a production manager, a senior technologist and the academic researchers; respectively the chemometric data analyst and a humanities scholar.

As the chemometric researcher presents his model in an illustration, rather quickly his illustration is met with skepticism. A delineation is made between the factory plant on paper (i.e., the design) and actual process manufacturing in a real-life setting. The process dictated by the laws of thermodynamics vs. what appears in a computer model. One of the managers points out that previous big data operations performed in their plant conflicted with what was physically possible suggesting that the type of correlation-based technologies may work for consumer behavior but not for chemical processes. Additionally, he argued, when the outcomes of process data operations do have something to contribute to the production process it seems that it is never a ground-breaking new insight but rather something marginal as adjusting temperature a few degrees, something that anyone who's familiar with the process could come up with. When the chemometric researcher falls back on the story about the multi-block model, he responds that indeed only where process knowledge is insufficient in solving the problem his process analytical tool would pinpoint where to look for clues, as he programmed underlying relations between the different components of the plant. After discussing certain characteristics that are specific to the production process in this factory plant, such as the relation between time and pressure, they fall back on the question- what new sort of information does the tool give us. Management underscores the importance that it is actionable. The chemometric researcher refers back to a previous meeting with technicians where it was suggested that his tool provides hints towards still invisible relations [among parameters and assets] as a form of troubleshooting. The senior technologist steps in and suggests that it provides the opportunity to dissect the production process postmortem when a badge has underperformed. This suggestion is answered by management that the model needs to be more robust and specific, and they all agree that the model is still to unshorn to be able to program concrete suggestions towards operators. And should for now be in hands of the technologist who can use it both to troubleshoot and refine the model (R&D dep.).

The former can be understood as constructive conflict (Decuyper et al., 2010); team learning can by means of dialogue integrate knowledge, competencies, opinions or creative thoughts (Burke et al., 2008; West, 2002). Depending on how team members deal with the expressed knowledge two different types of interaction arise: co-construction or constructive conflict. Constructive conflict is a process of negotiation or dialogue that uncovers diversity in identity, opinion, etc. within the team and leads to some kind of temporary agreement (Decuyper et al., 2010; Van den Bossche et al., 2006). Likely to lead to learning and conceptual advancement. As we can tell from the former both knowledge and responsibilities are being negotiated. This raises the question of why operators weren't invited when the postdoc asked for their attendance beforehand. This was answered with reluctance as the technicians engineers explained it was more difficult to arrange an online meeting with operators as they too have little access to online videocall platforms. Suggesting that perhaps there is a culture of not including workers here. Raising the question of whether and when operators can speak for themselves.

When asking for clarification as to why it is still too premature to present this tool to operators we were met with the following explanation. The plant manager clearly explains that in order for a digital technology to be implemented on an operator level all irritating-factors need to be removed. He explains that

(taken from our fieldnotes, loosely translated from Dutch);

> *if 'we', based on our experience in the production process, decide to raise the temperature even though we might lose some efficiency, we do not want to be notified about the temperature every half an hour. Our workforce consists overall of extremely conservative man; because they need to be! Both the repetitiveness of the job, and its additional responsibility, doesn't allow for experimentation but demands caution. More so, there is a very healthy kind of reluctance or even aversion to any kind of technology that isn't transparent.*[note - It seems as if the manager regards operators as the safeguards of the production process, that do so with vigilance.] *They do not need to be and definitely aren't eager or understanding for technologies that are still in an early stage of development or that takes 'learning'. However technologists (engineers) are eager and could use this (data-analytical) tool to interpret other findings and put them in concrete suggestions for the control room the next morning.* [note -What the plant manager underscores is that operators are being trained in terms of possible 'scenarios'.] *Their on the job training involves - What is the script, and what is your role to play. If the coffee machine were to break down on a Sunday afternoon at 4pm everyone would know exactly what to do, and who would be responsible. Thinking in terms of such scripts/ scenarios is in their dna, any innovation means altering that script.* [note - When being asked whether management operates in a similar mode they agree and call themselves conservative since their job demands that they prioritize safety]

When being asked what changes they foresee in terms of changing work environment

(taken from our fieldnotes, loosely translated from Dutch)

*Manager - We often see in production that innovations are perceived as an immediate threat to one's job. It used to be like that. Currently nobody is losing their job but I don't need to employ as much new staff as before. Inherently there will be less people in the shifts making their rounds, which implies a bigger load on the shoulders of individual operators, so they need to trust and rely on their own set of skill and knowledge. There is the fear to be solely responsible for the factory plant with only 3 workers.*

This manager talks about relying on your own set of skills and knowledge as an increasingly important factor in the operator job. Which is at the same time subject to change.

*Manager - A little malfunction in the plant should be sorted out by operators themselves. What used to be a leaky pipe; fix it yourself. Now it concerns a computer running a program; if it crashes at some point our people should be able to do something about it. The work is getting more abstract.*

Not only does this suggest that the newly developed technologies might risk the accumulation of responsibilities to certain operators. When the workplace itself is changing employees might find their respective duties object to change. Which begs the question; how much of the job will be re- scripted? And by who?

*Pharmaceutical plant*

In the pharmaceutical plant we meet with staff members online early 2021. In this department they can draw from their recent experiences with an innovation project concerning a data-analytic tool. We are met with a different tone; in a one-on-one conversation with a staff manufacturing process specialist, he describes a recent turn- around. Previously we would introduce a model and ask operators for their response; nowadays we ask whether there are issues in production that are difficult to identify and whether our model could be of help. Partly because the uncertain meaning of the output of the newly developed data analytical models were up for discussion.

In a different one-on-one conversation a senior lead data analytics describes how the problem of implementation had been three-fold. First, she argued, there had been the problem of infrastructure and the quality of the data, the preconditions for digital technologies to work. Second there had been the problem of suboptimal use of the technology, for tech to work it needs to surpass the implementation state and be integrated in its physical context. Third there was the social acceptance part where change management, according to our interviewee, had been crucial.

*'Rather than focusing on skill of the operator we first need better models. We have some models in place but depending on who [which operator] you talk to; its redundant; it doesn't give the alarms at the right time; 't's nice in some situations, but it doesn't save a lot of money; or human expertise is better'.*

She considers the quality of the algorithms as they are often black boxed- and considers knowing what to do with them. End-users are often forgotten, yet the quality of the algorithm should be judged by how it can be used on the shop floor.

*'The model 'works' only when user actually use them. Often a new model works well 'in theory', but the person who works with it is told 'this process needs your attention but I can't tell you why'.'*

She underscores that many of the models sound smarter than they actually are and emphasizes the need for feedback loops; the ability to disagree with the model. The operator job will become more analytical but it needs to become more interactive as well. Even for a more modern innovation environment she argues the current AGILE and SCRUM methods are more suitable for software or apps; *'it's [working with new model] not easy when you don't know what's in the data.'*

Danaher argues that technology often plays an important in determining the role-related duties within relationships. The former shows how data analytical tools (AI) might change the burdens and expectations within the work relationships in both plants. Here the AI model could potentially change the moral rules that apply within these relationships. Especially when parts become hidden i.e. black-boxed, uncertainty might alter expectations among different employees. '*These expectations form the basis of our role-related duties—the things we ought to do for one another. If we violate those expectations, we become targets of reactive moral attitudes: blame, shame, guilt and so on'(*Danaher & Sætra, 2023*;* Strawson, 2003*).*

*Relational*

*Changing the balance of power in relationships*

In general, when asking engineers ($n = 6$) about what is meaningful – often their answer entailed something that considered recent improvement projects. Whether its sharing knowledge gained in a long-lasting career or helping introduce novel technology as a younger more tech-savvy generation, engineers feel strongly about helping improve the factory plant. Engineers aim to improve the plant by digitalizing parts of the productions process that often concern operator proceedings. In the chemical plant this is described as a part of the job being pulled 'behind the wallpaper'. In doing so engineers in the chemical plant also seem to want to more strictly delineate the responsibilities of the operator to keep them from interfering with engineering problems. As one of the engineers stated;

*'well.. most operators have a lot of experience. But you should never take an operators word. In the entire shift of 30 operators there are like 4 or 5, of which you could say, they really understand the process. They could potentially educate themselves more but for some reason they are still there. The other operators reason from experience and not from understanding, but more like from their previous encounters with the technology. Their tinkering with how something works. That is of course of great value, when they figure something out, it gives us a direction to automate. But yeah in that sense, good relations with operators are important. When you want to try something out, you have to ask that operator like we can do either this or that. Without a good relation you can't work together..'*

Resulting in a trade-off between operators and engineers. Captured in this following statement.

*Engineer- "'Actually in my view, I think that those that sit behind the control panel, the operators, shouldn't change anything. They just have to sit there all day while the plant is running itself. Except if you want, I don't know, if something stops or there is an abnormality, but in principle the operator shouldn't do anything.'*

The statement by the engineer seems to result from him being responsible for the engineering process and not wanting others to interfere. Not only do engineers need operators to work in their engineered plant, but operators connect different types of technology and have assembled an entire set of skills to make the right information relevant at the right time. However, engineers see this differently and frame this as being redundant;

*Engineer- 'if you want to change the way operators work you got to have management support. I remember when I suggested that .. our panel-guy who usually writes a list of about twenty checks.. to automate this. To have those twenty items straight away, print it and that's that. But people had gotten really attached to that check-list, apparently it's important to them.. I guess… so we just didn't [laughs].'*

Technology can affect the balance of power within a relationship. As Danaher explains, relationships are rarely perfectly equal. Here the engineers have more power than the operators. AI might enhance these differences which has important moral effects. As it is argued as a mechanism that '*the powerful party typically derives more benefit (value) from the relationship and issues more moral demands of the other party. This* *can, in turn, generate considerable tension or instability in the social normative system. The weak may feel the need to rebel; the powerful may feel the need to reinforce their power, sometimes through draconian means'*(Danaher & Sætra, 2023). Indeed, AI systems have been criticized for being instruments of domination (Burrell, 2024).

*Perceptual*

*Changing perception*

Starting our ethnography fall 2020 in the chemical factory we wanted to understand what work in these premises was like. The operator gave a remote tour around the site (outside) using a tablet. While showing his surrounding he would tell what he would be doing and we were able to ask questions. The operator indicated that him walking his 'rounds' is intended for safeguarding the premises by means of walking through all the steps of the production process. We 'walked' past big silos, taking stairs along large metal installations, heaters and coolers, where all sort of reactions take place. Each production step also yielding different by-products in different states of matter (be it liquid, gas and so on) which then would be telling for the type of activity the operator would have to perform in terms of checking temperatures, pressures and leakages. For example in the chemical plant the protocol to deal with a potential membrane leakage in one of its huge installations involved an intense eight hours shift of 'washing' and 'soaking' performed in pairs (two operators). The operator also showed how he would take samples and bring it to the lab, to analyze the samples himself. What he showed was one of the few in-door facilities where operators could group together and hang out.

When we continued our ethnography spring 2021 in the pharmaceutical company in a similar manner operators on the shopfloor (indoors) would guide us through their work routine while holding a tablet. They showed how they would read out different parameters from the monitoring unit of the bioreactors; large tank-like installations. One of the operators would reason out-loud about consecutive steps based on their knowledge of the process and the numbers presented. Like diverging from routine steps when possible contamination had taken place based on their reading of oxygen levels and acidity (pH). Operators in the pharmaceutical company, after implementation of a newly developed data-analytic model, would have to read their most important parameters supported by an additional interface and thus expand their line of reasoning in terms of graph reading, reading color coding and such. However, this wasn't successfully integrated within their routine. Losing perception of the production process seemed to limit their argumentative strategies and thus reason to reject the technology as a whole. In this interview held with a senior operator in the pharmaceutical factory plant we discuss the new tool;

{$R$ = Respondent, $I$ = interviewer)

R - *Ideally to use [DATA analytical tool] we need two screens. One for the monitoring tool and one for our regular process management. But I can't keep watching that screen for 8 h straight, that doesn't work. Of course I set these alarms that I receive in my email; but I can't keep checking the program. That's a big downside, I can't keep checking the tool continuously.*

I- You don't use the program to monitor but to diagnose?

R- *Yes, definitely. I try to* log *in, I use to do that every day but that was getting less and less. I look at all the alarms, and whether I can fix those. What are they signaling and do they influence the process. Then I reset the alarm. We use to do it every day, Now I'm the only one to still* log *in. My colleagues have stopped trying.*

I – No? did you experience any benefit?

R- *In the beginning it provided a lot of benefit. I was working in the other building and there was an issue with the* pH *let's say. It wasn't noticeable on the [regular monitoring tool] but I did receive an email from the data analytic tool that the* pH *was dropping. I went to check and I could resolve the problem fairly soon and that was a great, great… I was looking at the screen coincidentally. We need a big screen with [data analytical tool] on it. An overview. We have the means but it's not being used.*

Later on.

I - What would you need?

R – *you know, we get alarms continuously on the [monitoring unit] . One of the alarms goes off when the* pH *drops below [a certain number]. Only when it drops below the alarm goes off. I'd rather have the alarm go off sooner when we know in time what it's doing, that its dropping,*

I- So you'd rather know something in terms of dynamics?

R- *Exactly; they did develop something like that but you don't know what the alarm is for. But at least in [new data analytic tool] I can compare batches. That's is a big plus.*

The interviewer continues with questions concerning how overall change was managed. Our interviewee explains how new technologies acquire them to incorporate all kinds of new activities

I - Did you ever experience resistance to change?

R - *When I came here [16 yrs ago] some operators had been working here for over 10 years; when change occurs, they are a bit against it because they had to learn and apply new things. They are not afraid to lose their jobs but these technologies are of a higher skill level than they are used to.*

I – did it become more complicated?

R- *actually new technologies make our work less heavy, we used to have to do the cell count individually, we don't have to do that anymore'* …

*'new technologies do takeover parts of the job but they do also deliver new work. Whether its cell count or measuring PH that is being taken over, I would still have to install the probe in the bioreactor, carry out verification procedures, control its measurements whether it's working correctly. We still have to do all those things that's more not less,'*

The senior operator points out how the different procedures need to be tied in to the overall process. Data analysis is something that is constantly done by operators within the factory plant, by very carefully, setting, draining, re-installing, measuring, manipulating, checking and negotiating the analysis can be made.

In both companies the operators are able to balance the parameters against what they know about the different type of equipment and its settings in the factory plant. Although the operator-job seems to entails scripted proceedings, their experience with the equipment and their work environment feeds into the evaluation of the steps in the protocol. The individual employee negotiates production protocols, managerial authority, social norms and commercial interests. The individual operator attempts to provide overall coherence: stories linking his actions to the chemical process, engineering logic, the production output and their on-the-job social life; these multiple forms hang together, not as a coherent whole, but as a "patchwork" (Gardner et al., 2011; Mol, 2002). Not only does this mean that each professional, each job, is differently assembled. When AI will alter how the different data streams are handled; what employees base their actions on is to be negotiated. By implementing a data analytic tool operators have to redetermine how to perceive the production process and discern whether and how to operationalize these perceptions.

As Danaher & Sætra argue '*One thing that technology can do is provide us with mental models and analogies for understanding the world.*' Understanding ones job in terms of 'handling data' alters how we asses our options. Where previous 'mental models' were framed in terms 'thermodynamic laws' understanding ones job as data handling might affect moral rules: actions we once thought were permissible become clearly unacceptable and vice versa (Danaher & Sætra, 2023).

## Discussion

Ethics parallel research has led us to describe techno-morel change in process industry. Currently industry 5.0 is in the making by actively pursuing human-centric AI. Our qualitative research in process industry explored consequences of the implementation of AI. Our observations suggest that AI is at risk to impact workers in three ways, the so called soft impacts that need to be navigated to foster human-centric AI.

1. C**hanging the burdens and expectations within relationships -** Discussions about a process-analytical tool revealed tensions between technological innovation and what was characterized as the cautious, scenario-driven mindset of operators, who surprisingly were excluded from the conversation. As the plant evolves, operators may face more abstract challenges, such as troubleshooting computer systems, adding complexity to their roles. This shift raises questions about how much of the operator job will change and who will control this transformation.
2. C**hanging the balance of power in relationships -** Engineers focus on improving the factory plant by digitalizing processes, often to minimize operator interference, which some view as detrimental to engineering tasks. While operators bring valuable experiential knowledge, depending on the work environment engineers can either limit or promote operator involvement. This reveals a power imbalance where engineers hold more authority. The potential for AI to amplify these disparities raises moral concerns, as the more powerful party (engineers) may demand more (or less) from the less powerful (operators), creating tensions.
3. **Perceptual** - Operators use technology to monitor and manage production, but their deep knowledge of equipment and process is essential to interpret data and make decisions. Work for an operator is being able to orchestrate different aspects of the job that coincide with ones idea of what our technical surrounding means. It is exactly this heuristic aspect that is subject to change as AI tends to capture all aspects of the production process in terms of data streams.

What could these mechanism of techno-moral change in process industry mean? This raises the question of what the moral and practical implications of technologically-mediated moral change could possibly be (Nickel, 2020; van de Poel, 2021). Nickel argues that when we are uncertain in face of moral ambiguity we encounter moral disruption (Nickel, 2020). Such disruption should be considered a serious impediment to individual moral agency; blocking people from knowing their own moral obligations and the obligations of others. The author argues we can mitigate such harm by creating stability and dialogue (ibid.). Van de Poel identifies three technical features that can designed into systems so that they are better able to deal with value change: adaptability, flexibility, and robustness (van de Poel, 2021). While our findings are limited in terms of size and generalizability, it does suggest researchers in the field of AI ethics should conduct more elaborate empirical studies of human-AI relations in practice to identify moral uncertainty in AI development. Ethicists should look into ways to integrating such findings to stir mechanisms of techno-moral change towards 'good' AI usage.

## Conclusion

In this article we aimed to provide ways to take into account soft impacts of AI that industry failed to consider in I4.0 in order to stir towards I5.0. Our 'ethics parallel research'- approach has led to further investigate the vulnerable position of workers within these industries. We started out by pointing out the strained relationship between employees and newly developed AI technologies within process industry. Additionally we highlighted how AI innovations have been criticized for not being able to pursue broad-based prosperity nor meaningful work. We raised two research questions: First (RQ 1) - How do workers in process industry currently interact with their socio-technical surrounding? Second (RQ 2) - How would AI potentially affect these relationships? What we showed was subtle but important differences that come with the respective job related duties. While engineers continuously alter the plant as being a technical system; operators hold a rather symbiotic relationship with the production process on site. Building on the framework of different mechanisms of techno-moral change we highlight three ways in which workers might be (morally) impacted by AI.

1. Decisional - Alongside the developmental of data analytic tools respective roles and duties are being decided; operators should be involved in the development of AI
2. Relational - Data analytic tools might exacerbate a power imbalance; operators should be able to provide feedback during the implementation of AI.
3. Perceptual - Data analytic technologies mediate perception; operators should be able to adapt the AI system to be able to shape their perceptions of and their relation to the production process.

While in I4.0 the problem is framed in terms of 'suboptimal use', in I5.0 the problem should be thought of as 'suboptimal development'.

## CRediT authorship contribution statement

**M.W. Vegter:** Conceptualization, Data curation, Methodology, Writing – original draft. **V. Blok:** Writing – review & editing, Supervision. **R. Wesselink:** Supervision, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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