Tensions in the transition of Human-AI Collaboration: A Case Study of the Nordic Renewable Energy Sector

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Abstract

The increasing trends of developing and using artificial intelligence (AI) in organizations and industries are not without consequence to work practices. Theoretical suggestions for humans to collaborate with AI clash with the empirical studies, which highlight problems with implementing and using AI systems. We investigate this phenomenon through the practice lens of tensions in a Nordic renewable energy organization's digital transformation (DT) effort. Following an ethnographic case study, we uncover four tensions experts feel across knowledge boundaries in group collaboration settings, disrupting normal work practices and taxing additional organizational resources. Through these tensions, we reflect on the softer and less dramatic changes and dynamics of human-AI collaboration for emerging work practices and DT in an organizational setting.

Keywords: Human-AI collaboration, tensions, work practices, ethnography, digital transformation

1. Introduction

Artificial intelligence (AI) is a concept that has existed since the 1950s. However, recent advances in processing power, storage, computing techniques, and big data have propelled AI to the forefront of innovation. AI has also reignited interest among organization science and information systems (IS) scholars. Proponents of AI adoption envision that AI creates value for business and society. In contrast, others are skeptical of AI's advertised benefits and call attention to the harmful effects of AI applications. Some examples include human biases transferred to algorithms, (Mehrabi et al., 2022), environmental degradation due to increased mining (Crawford, 2021), unemployment (Iansiti & Lakhani, 2020) and loss of human dignity due to algorithmic control (Griesbach et al., 2019). At the core, however, both sides demonstrate the potential of AI to impact industry and society, changing how we live and organize (Mikalef & Gupta, 2021).

The emergence of AI's extensive use in public and private sectors has shifted the focus to the arena where AI works within organizations and is juxtaposed with organizational processes, structures and employees (Fügener et al., 2022; Jarrahi, 2018). The computer science perspective on AI and work focuses on better-performing algorithms and optimization. At the same time, organizational scholars are concerned with changing work practices and the loss of jobs due to AI automation (Iansiti & Lakhani, 2020). There remains a scarcity of empirical studies showing the measurable impact of either widespread loss of employment or stellar improvement in performance with AI systems (Furman & Seamans, 2019; Grace et al., 2018).

Adopting ready-to-use AI systems highlights the problem of epistemic uncertainty—doubt over ground truth labels and insufficient explanations. This uncertainty could be mitigated if AI systems were made with users' needs, domain experts' knowledge, and facilitate transparency of decision-making. Therefore, assumptions can be made that in-house or custom-made AI systems may not share the same epistemic disadvantages as out-of-the-box AI tools. Extant literature on human-AI collaboration is scant in this perspective (Autor, 2015; Furman & Seamans, 2019; Grace et al., 2018). Some empirical studies show human engagement and disengagement with AI as part of the technology use (Lebovitz et al., 2022; Waardenburg & Huysman, 2022). However, there is less focus on human participation and attitude while designing and developing custom-made AI systems.

Algorithmic work, including auditing and altering data and algorithms, has demonstrated clear needs for human, AI, and human-AI collaboration requirements (Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021). There is much to be understood on how humans and AI as a hybrid learning system co-evolve in organizations. There has been a call from academia to explore human-AI systems as collaborative and co-creating rather than co-existing systems (Waardenburg

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& Huysman, 2022). In this line of enquiry, socio-technical and practice-based lenses are better suited to observe the evolution of transformation of human-AI work practices.

Digital transformation (DT) is credited with value creation in strategic business models that usher in more pronounced changes in human work practices, skill requirements and organizational structures (Acemoglu & Restrepo, 2019; Sampson, 2021; Scott & Orlikowski, 2022). The process of DT is often described as a 'radical' or 'dramatic' process (Hinings et al., 2018; Vial, 2019). Yet, Orlikowski and Scott (2022) have recently drawn our attention to the 'digital undertow' as a metaphor to understand the unknown, unintended, but continually felt displacements of book industry standards as part of DT. We seek to zoom in and examine a softer angle of the subtle forces of change that are part of DT at the organizational level, such as leadership, organizational culture, work practices, and employee attitudes. Recent calls from academia to explore nuanced processes in human-AI collaboration provide justifications for exploring the actual interactions that occur when organizations create and integrate AI systems into their existing organizational work, culture, and processes. Therefore, we pose the following research question: *What tensions in organizational work practices emerge during human-AI collaboration?*

Our paper examines AI's emerging changes as part of the DT narrative by looking at the softer flutters of the DT process between knowledge workers and an in-house and under-developed AI system. We refer to these small yet inevitable changes as creating tensions and to the early occurrences that are almost invisible to differentiate from the norms and routines in work practices. We argue that these tensions are an expected part of the process, contributing to a softer understanding of the dynamic nature of DT and emerging research on human-AI collaboration.

2. Research context

2.1 AI and digital transformation

DT has had many proposed definitions to encapsulate the enigmatic, confounding, and multiplex nature as distinct from other similar processes, such as IT-enabled change (Vial, 2019; Wessel et al., 2021). At its core, however, DT can be understood as "[a] fundamental change process, enabled by the innovative use of digital technologies accompanied by the strategic leverage of key resources and capabilities, aiming to radically improve an entity and redefine its value proposition for its stakeholders." (Gong & Ribiere, 2021, p. 12). Within IS literature, increasing attention is being paid to the resource demands of AI (Chowdhury et al., 2023; Mikalef & Gupta, 2021) due to the accumulating adoption of AI in organizations and the underwhelming generation of business value despite the promises of AI (Fountaine et al., 2019). For many scholars who have worked on DT, there is a harrowing similarity to this rhetoric, as adopting any digital technology (including AI) is not enough. Instead, DT success is a custom recipe that accounts for aspects such as digital business strategy, organizational culture, and leadership (Osmundsen et al., 2018), all in alignment with the innovation of the chosen digital technologies. Leveraging AI for DT requires an organization to redefine its value proposition while reconciling with disruptions to its work practices (Wessel et al., 2021).

In many ways, AI and algorithms as digital technology differ from other traditional technologies (Berente et al., 2021; Kellogg et al., 2020). Especially as AI continues to inch closer to human-like intelligence, the opportunity for machines to make data-driven decisions, take actions with human-impacted outcomes, and, most importantly, learn (Marr, 2020) is of tremendous relevance to digitally transform organizations, society, and industry. However, these entities must have the resources necessary to support DT, such as specific skills for developing AI expertise among employees (Trenerry et al., 2021). AI has considerable barriers to success, especially compared to traditional IT projects. They stem from AI's need for data, which demands resources from the organization, a high degree of specialized technical capabilities among employees, and management competence (Bérubé et al., 2021).

These barriers underline that AI is not a standalone technology but instead entangled in human factors (Marr, 2020) with significant resource dependencies. On the one hand, the technical resource requirements to ensure a variety and volume of data to feed the AI system must be supported by infrastructure to perform the algorithmic and data-related work. Determining to what degree AI tools can automate or augment (Chowdhury et al., 2023). More human abilities, such as technical skills and tacit knowledge (Mikalef & Gupta, 2021), further emphasize the socio qualities in AI implementation and adoption success for organizations.

2.2 AI and human work practices

Human and AI intelligence have distinctive advantages in dealing with complexity, uncertainty, and equivocality. Literature on AI augmentation and automation highlights humans in- and out-of-the-loop perspectives (Raisch & Krakowski, 2021; Zanzotto, 2019). Many studies have argued that removing humans entirely from the loop is more challenging, especially for critical decision-making such as medical diagnosis. IS and organization science researchers emphasize the irreplaceable role of humans in decision-making that may directly impact health, human rights, and society. Therefore, a hybrid human-AI balance is being discussed to address these forthcoming challenges (Zanzotto, 2019). However, careful consideration of an algorithm's impact on human knowledge, control, and occupational boundaries is necessary (Faraj et al., 2018).

Some studies have accentuated the differences between human and machine learning methods as substantive and formal logic at play (Leavitt et al., 2021; Lindebaum & Ashraf, 2021). Nonetheless, humans co-exist with AI in the same work environment, developing coping strategies to manage the human-AI collaboration (Grundstrom et al., 2023). Literature on the future of work with AI indicates that new configurations, conceptualizations, and purposes may generate unforeseen consequences when AI and humans work side-by-side (Baptista et al., 2020; Waardenburg et al., 2022). Therefore, there is a need to understand the nuanced human-AI collaboration in varied organizational contexts (Lebovitz et al., 2022; Suresh et al., 2021).

Specific to knowledge workers, many recent field studies have indicated that experts employ varying practical strategies of disengagement, engagement, symbolic acceptance and brokering knowledge to adapt AI results to their work practices (van den Broek et al., 2021; Waardenburg et al., 2022). These studies have moved the argument in the right direction of inquiry, which is core work practices shaping AI-human hybrid systems. Still, they do not encapsulate early developmental work on AI within the organization. Some disruptions are inevitable when a new technology becomes part of the work processes. Then, managing changes with AI during developmental work becomes as essential as creating or implementing the system.

3. Methodology

3.1 Ethnographic field study

Our ethnographic field study is carried out within a renewable energy production organization (hereafter EnerX) which has been operating in Nordic countries since the 1950s. EnerX's wind farms are located on rugged mountainous terrains, and because of these extreme terrains, monitoring and maintenance of wind turbines have become increasingly difficult. The Internet of Things' presence has helped the company to oversee these remote assets. This new arrangement has also brought novel resources to EnerX, such as vast amounts of high-quality sensor data and new knowledge generated from data analytics.

The main AI artifact of our study is the condition-based monitoring system (CMS), which is also where the ethnographic data was gathered. The in-house CMS system (hereafter aiCMS) has been in development since early 2021 and feeds on the sensor and SCADA (Supervisory Control & Data Collection) data collected from each turbine. Traditionally, monitoring and maintenance of wind turbines was manual work where technicians physically visited to check the health of various components. By attaching sensors to the components, data is collected in terms of vibrational frequency (m/sec^2). This data is critical to understand when the vibrations show good health and when an increase/decrease in the trend indicates underlying problems. Additional information on variables such as temperature, wind direction, or blade angle are collected from the SCADA system.

Digitization of the wind turbines is not a new concept for EnerX. However, remote monitoring and predictive maintenance are novel value propositions brought forth by the in-development machine learning (ML) models. aiCMS, as a predictive and monitoring AI system, provides a unique opportunity to conduct a field study as it qualifies as a critical industry application and an ongoing project within the organization. Therefore, aiCMS provides a context to understand the tensions of human-AI collaboration during the in-house development of aiCMS. The case also affords the opportunity to study the phenomenon as it unfolds.

3.2 Research approach and data collection

An ethnographic field study following the interpretive research paradigm was conducted (Walsham, 1995). We adopted this approach to uncover the tensions between knowledge workers and other experts in EnerX to examine the human-AI collaboration effects (Mikalef & Gupta, 2021). The initial fieldwork was conducted from January 2023 to May 2023. We started the study when aiCMS was partially launched for three months within EnerX, after 18 months of developmental work. The study period covers the overlapping design, development, implementation, and usage stages. To receive early and intentional feedback on use, one wind farm was selected where its site personnel were encouraged to use aiCMS.

For construct validity (Yin, 2009), triangulation from different data sources was gathered through observations, self-journaling, interviews, and documentation (Table 1) in a longitudinal manner (Noble & Heale, 2019). Seven interviews were conducted with various experts (Table 2), along with observational data from the fieldwork. The first author gathered all the data.

Table 1. Data sources.

Data Source	Description	Details
Interviews	Semi-structured interviews	7 interviewees, 58 pages of transcriptions
Observations	Field notes, reflections, and observations captured during or immediately after field visits, meetings, and casual interactions	20 observation participants, 56 pages of field notes, 31 days of field observations
Documents	PowerPoints and similar documentation about aiCMS project	65 slides, and 30 pages of documents

Table 2. Participant Characteristics.

Interview and observation participants			
Name*	**Role**	**Name***	**Role**
Stian	Technical manager	Olav	Turbine technician
Nora	Technical manager	Hans	Turbine technician
Qiang	ML engineer	Bjørn	Product manager
Lars	Technical Analyst	*Pseudonym given to all participants for anonymity	
Observation Participants			
Name*	**Role**	**Name***	**Role**
Sven	Site manager	Harald	Chief AI officer
Dag	Site manager	Huan	ML engineer
Jennifer	Work process manager	Shama	ML engineer
Gene	Work process manager	Ingrid	ML engineer
Sarah	Work process manager	Emil	ML engineer
Stefan	AI manager & developer	Eric	ML engineer trainee
Adam	Head of management operations	*Pseudonym given to all participants for anonymity	

3.3 Data analysis

Data was analyzed in two phases. In the first phase, we conducted an inductive process analysis following (Berends & Deken, 2021). This method was used due to the interest in understanding the dynamic nature of human-AI collaboration over time, and mapping different phases sequentially helped to situate the temporal nature of the case. In the second phase, inductive concept development was used (Gioia et al., 2013). Comparisons between first-stage concepts with literature on DT, work practices, and knowledge management related to AI were performed. Dedoose software v9.0.62 was used for coding, where seven transcribed interviews, observations and reflection notes containing interpretations, and document analysis on fieldwork were uploaded. A qualitative process analysis was also followed by (Langley & Tsoukas, 2016) for setting boundaries to the data and selecting a sub-sample of the data that focused on work practices, group interactions, and DT in the human-AI context. The first two authors discussed the concepts, coding, and data theory iteratively to develop the four themes that narratively describe the tensions below.

4. Findings

4.1 Tensions felt in knowledge boundaries

The AI project, aiCMS, started as any other exploratory project in EnerX. It aimed to change value propositions by utilizing existing local resources such as human expertise and big data. Bjørn, the product manager, had a specific set of goals and knew how to navigate projects with his extensive project-management expertise. For aiCMS, the business goal was clear from the beginning: 1) to create value from existing big data and 2) to reduce the outsourced dependency on data analytics. However, the process to reach the goal was not clear. The core members of the project team were the product manager, Bjørn and an ML developer named Qiang, who were later joined by the site manager, Sven, and technical managers, Stian and Nora. Throughout the timeline of aiCMS, the project team has experienced what we identify as tensions to the knowledge boundaries of domain experts. We describe these tensions to happen in the context of project management for aiCMS.

During the developmental stage of the aiCMS, the product owner questioned his knowledge and capabilities for the role. The disruption from lack of knowledge or feeling of inadequacy motivated him to learn more about ML and programming.

"I think I have to spend some time to become more familiar with the [machine learning culture]. And in the AI department, to get to know what they are doing, what is (their) interest area, what is machine learning?" - Bjørn, Product owner

Similarly, practical knowledge about wind turbines, internal workings and situational awareness of the physical systems were necessary for Qiang to build a robust AI system. Qiang visited the wind farms multiple times in the early days of aiCMS to expand his knowledge. He was keen to understand some of the environmental factors that could affect ML models' performance, and these visits provided him with contextual knowledge previously outside of his areas of expertise.

The rest of the technical team also faced some form of knowledge inadequacy when exposed to aiCMS. Their engineering domain expertise seemed insufficient to understand how the AI system was developed, what these ML models can predict, how to interpret aiCMS' results for monitoring work and what corresponding actions should follow from analytics. For example, when ML models predict an increasing trend in vibrational frequency for a component, it indicates that one/many sub-parts of that component are dysfunctional. The increased vibrational trend analysis alone is insufficient to understand the causes of failure. In this scenario, Qiang performs spectrum analysis, transforming the sensor signals by a fast Fourier transform (FFT) algorithm to produce another frequency graph. Compared to a healthy corresponding component's graph, this can reveal whether the component is truly faulty. For this sophisticated interpretation, technical engineers need to expand their knowledge of sensors, locations and relative positions of components, and master knowledge to read FFT graphs to diagnose faults correctly. This learning is critical for deciding when to replace, repair or discard components.

From an occupational boundary perspective, experts with specific engineering disciplines did not specialize or have the right resources to work with aiCMS effectively. The product owner of aiCMS, Bjørn, was intimately involved with building the data infrastructure, streamlining the data flow, defining alarm levels, and translating the complexity of ML models to other stakeholders. This turned out to be one of the most difficult projects, and it has challenged him and his expertise as a project manager.

"I had to realize that I could not understand everything, but I can discuss the output and also need to understand a mix of domains with ML. So even though this is a small project, it is quite complex for me. I had to agree with the management groups, then I had to translate the complexity of the models and of the system to someone at the management group to understand and to see the value of the system (aiCMS)." - Bjørn, Product owner

4.2 Tensions felt in group collaboration

A clear roadblock in the aiCMS project became evident when some team members disagreed on the project's operating phase. For example, the technical team disagreed when discussing moving aiCMS from the development phase to the product phase and to launch for all site personnel of all the wind farms. Even though the group members regularly met, discussed, and shared feedback on varied topics, including report generation, alarm levels, interface improvements, etc., they had completely different mental frameworks on the AI system's maturity level. A clear lack of a common language should have helped reduce confusion and misunderstanding in the group (Waardenburg & Huysman, 2022). These fundamental gaps in understanding where aiCMS stood as a project has created consequential developmental roadblocks demonstrating clear tensions within the team. The tensions have challenged the established collaborative practices and threatened aiCMS' implementation plan.

Disagreement on various standards and existing metrics was prominent among the technical team. Whether some of the sensor signals were to be included and interpreted for anomaly detection was heavily debated. Frustration was evident whenever their core domain knowledge of maintenance and monitoring seemed inadequate for the new way of predictive maintenance created by aiCMS.

"So, if you look at this gearbox here, you see it was red and these are all the signals from this gearbox. [...] So, we don't use time on it right now. So even though it was red on the front page, I will not look at it. Because it's not a frequency spectrum, we don't understand it yet. So that's why it's hard for me to sit here and use [aiCMS] right now. It's better to get these emails and check the ones I can understand." Lars, Technical analyst

The AI system disrupted the expected project management process and challenged knowledge workers' expertise and occupational responsibilities. On the other hand, Qiang's knowledge expanded from the site visits and helped create the ML models resembling real conditions. Additionally, mistrust in the alarms' notifications due to the oversensitivity of AI models is embedded in the core disagreement and tensions that the team faced. Which also contributed to an increase in the complexity of actions needed after the notifications were generated. Hence, verifying and validating the problem's source increased the work complexity and collaboration among the team members when AI was in the loop.

Coordination and collaboration among the team members changed because of tensions arising with alarm levels. Four alarm levels from 1-4 were set according to the increase in upward trend (standard deviations) from the baseline. However, due to the nature of algorithms' learning, i.e., from the historical data, it took a long time to learn baselines and find each component's natural behaviour pattern. In this waiting period, the technical team grew impatient and was disappointed with the overall performance of AI predictions. They suggested that simulations could have expedited the learning of baselines and improved ML models' performance.

Another example of collaboration tensions was regarding events related to repair and replacement. When some components were replaced or realigned, or sensors were relocated to and from their initial positions, updated information needed to be shared with the ML team, for example, the date and time of replacement, the exact new location of the sensor, and update on additional information. The ML team called this information "event data," and they created a separate (CSV) file where they kept track of changes. Including this event, data directly moderates the prediction quality of the models. The dynamic data, or lack thereof, indirectly impacted their work practice, such as the additional coordination effort needed for updating event data. If the site team failed to share the event data with the ML on time, then the number of incorrect alarms and warnings generated by aiCMS increased. These alarms needed further validity verification and validation from the site team, leading to additional work for the team.

4.3 Tensions felt in the established working practices

Technical analysts were observed creating shadow practices to perform generic tasks of "diagnosis of alarms and warnings" with some local Excel sheets. These actions challenged normal working practices and created tensions between the analysts and other employees. For example, when they receive an email notification (generated from aiCMS' ML model predictions), they collect some basic information, such as turbine number or initial descriptions of the failure, and then begin a five-step process to diagnose the cause of the notification. Instead of looking at the alarms at the in-house digital interface or one of the vendor interfaces to confirm the source of the problem, they follow a complicated self-generated verification and triangulation process. First, check the in-house digital interface; second, contact the site personnel; third, check work orders at another in-house interface; fourth, check the digital interface of the aiCMS; and finally, check the vendor's digital interfaces.

Work practices of developers, project managers and users have been disrupted by the challenges that an AI system brings. The involved actors went through three phases to work with the AI. First, by adjusting their work practices and self-reflection, the actors tried to understand their roles and responsibilities in the human-AI configuration. Second, they tried to gain insights through immersion, encapsulation and discovery of new knowledge and gain confidence from their understanding and their awareness of the impact of the AI results. Third, from their renewed experience and insights from working with AI results, the domain experts suggested improvements to aiCMS, specifically to recalibrate model parameters and validate output.

Disagreement on standards, baselines and accepted metrics existed all through the development and feedback phases of aiCMS. There was disruption to the workflows of the teams' practices with AI outputs. The vendor sent notifications about failures in the previous arrangements, with trend analysis and recommended actions. Additionally, the vendor trained the turbine technicians to use their numerous digital interfaces as part of the training. The vendor also shared an exhaustive list of possible failures in a PDF document at the early stage of wind farm development.

Hence, when a problem surfaced at the turbines, the on-site team knew the workflow towards solutions. In comparison, aiCMS generated outputs, reports, and graphs on the digital interface, creating ambiguity in the problem-solving process. When the aiCMS team shared PDF reports containing some recommended actions, the maintenance team was uncertain how to respond to this information. Because the maintenance team knew from experience that the set limits of the alarms were unreliable, and recommendations that came with the alarms were automatically generated. Hence, they were uncertain to follow regular work procedures.

"I don't know aiCMS. What I expect from aiCMS is that it will be more reliable. We have a lot of alarms and it's really that no one verified this from aiCMS. It is automatically generated." Nora, Technical manager

Verification and validation were additional steps, along with their interpretation and pre-selection of which information to work on. The recommended actions of the AI-generated reports lacked legitimacy on track record and a good reputation for quality. The recommendations were not supported by documentation or established knowledge shared with the team, causing tension.

4.4 Tensions felt by the organization

Attitudes towards automation and the capability of AI have largely been optimistic by employees at EnerX. However, evidence of unrealistic expectations from AI has led to disappointment. The transition of aiCMS project from the development to the implementation phase should have occurred according to EnerX's practices. Still, tension was evident across EnerX when the new system was introduced. A vendor-made system (non-AI), adopted five years ago, saw resistance to change and took many years for EnerX to adopt fully; tendrils of this resistance are still felt throughout the organization.

"It took the process management team several years to build the trust in system Xafi. Because if people experience errors even once, then reliability drastically reduces, and it becomes harder to build trust among users again." Indirect quote from Sarah, work process manager

Time has an emerging role in the human-AI hybrid work environment. Although preventive maintenance is future-oriented, many actors still perceived AI in its classical automated intelligent system form and looked further into the future. This may contribute to the over-optimism and unrealistic expectations from the available AI system.

For the experts, accepting AI-based decision support in their regular work and understanding that their active participation is needed to complete tasks could be helpful. For AI systems, when predictive analytics can generate fine-grain analytics for the knowledge workers, interactive and reactive responses from the experts can help refine the system (Grønsund & Aanestad, 2020). This interaction can help learning algorithms access better-quality data and new knowledge from experts. However, the organizational culture did not facilitate this change and the strategic shift from reactive to preventative maintenance.

Challenges of data as a resource have also become a source of tension for the organization. Disruptions were evident in four key areas: when available sensors do not collect information on all parts of the turbine (incomplete information), when the AI predictions do not match reality (incorrect predictions), when AI models falsely identify failures, or when training data excludes references. The consequences of unreliable information from the AI system made the actors search for relevant information elsewhere, increasing the search cost for the organization and amplifying organizational resistance to change in the process.

5. Discussion

5.1 Tensions of digital transformation

In this article, we asked: *What tensions in organizational work practices emerge during human-AI collaboration?* We uncovered four main tensions through the process of human-AI collaboration. We discuss these findings considering theoretical and practical implications for researchers and organizations facing the human-AI dilemma as part of their DT.

Using tensions to understand the softer disruptions occurring in organizations and at the socio-technical meeting point of humans and technology has long been a valuable lens for the IS discipline (Marabelli & Galliers, 2017; Orlikowski & Scott, 2021) and DT (Koukouvinou et al., 2022). Tensions created by AI and considered in light of socio-technical applications are a call of interest for responsible AI (Vassilakopoulou et al., 2022), digital innovation (May, 2020), DT (Rowland et al., 2022), and decision-making in human-AI collaboration, ultimately requiring further extension as research on AI is emerging continually. We contribute to this discussion on tensions by identifying four during human-AI collaboration in a Nordic renewable energy organization.

Across the four tensions—knowledge boundaries, group collaboration, during work practices, and by the organization—evidence of EnerX's capability to implement and adopt AI through tangible, human, and intangible resources was evident (Mikalef & Gupta, 2021). However, there was a heavy focus on the technological side of the equation and an apparent lack of more intangible resources such as inter-departmental coordination (Fountaine et al., 2019) and low degrees of organizational change capacity. Reconfiguration of work processes, systems and human resource management can contribute to the adaptive capability of organizations. Leadership support can help trigger the integration process required for AI systems to integrate into the organization's daily work, decision-making, strategic planning and thinking. Top management's resource allocation prioritization for human and machine motivation and acknowledgment could be critical for organizations' co-evolution with AI systems.

Defining the value propositions of AI is necessary in the DT process for organizations (Gong & Ribiere, 2021). Among several ways to create value from AI systems, EnerX has a new value proposition of preventative and predictive maintenance, differing from corrective maintenance (Wessel et al., 2021). Data has strategic value for EnerX as it is an essential resource for training and continued learning of aiCMS. Hence, data could be generated with instruments, analytics, processes, or human decision-making in this new arrangement of human-AI co-existence.

Moreover, taking strategic actions from AI-enabled value propositions could also depend on translating new knowledge and the speed of distribution across the organization. In the tensions felt by the organization, data for the AI system was incomplete, leading to incorrect predictions, further propelled by inaccurate data collection for the learning algorithms. Data-related tensions compounded with employees' loss of confidence in the new system can contribute to organizational resistance and low change capacity essential for DT (Hanseth et al., 1996). For these reasons, practitioners should look at organizational resources holistically, as the tensions are inextricably bound together, moving from technical to human, data to disappointment. Culture in an organization is just as influential as technical infrastructure to realize DT.

Our findings also resonate strongly with changing how we think about research on AI in organizations (Waardenburg & Huysman, 2022). While blurring the boundaries between traditional groups during collaboration has caused tensions (tension 2). We see these tensions as precursors to bigger change that are harmonious with the need to release the separation of development and use theoretically, working towards the blending interpretations of co-creating AI at work.

5.2 Tensions of work practices

IS theorists have proposed recent work on AI and human work as a hybrid system that has been well accepted (Bailey & Barley, 2020; Lyytinen et al., 2021). With some exceptions, (van den Broek et al., 2021; Waardenburg et al., 2022), most scholars look from either the data scientists' perspective or the users' (Wang et al., 2019). A holistic perspective on a team provides insights into the changed work practices at the early stages of development and use. A diverse team exposed to the AI systems in their organizational setting and regular work practices can show the nuanced changes. While our study demonstrates tensions between the collaboration between humans and AI, the workers' attitudes are mostly positive. Other studies show more extreme resistance to human-AI collaboration, such as Jiang et al., (2021), who examine knowledge workers for qualitative research analysis, emphasizing human autonomy in the process over AI involvement.

The first tension felt was in the knowledge boundaries of the knowledge workers who were put off by their AI-related limitations. Accordingly, they sought new, contextual, domain-specific information to cope with their self-identified insufficiency. As human resources for AI require technical skills is an often-identified challenge for organizations (Chowdhury et al., 2023), this exemplification of epistemophilia is a tactic demonstrated by those embedded in knowledge work. They were challenging the silos of knowledge and the traditional boundaries assumed in software development. Boundary crossing between developer and user is relatively easy within the same communities (Waardenburg & Huysman, 2022).

This justifies a need for a group of diverse domain experts who work with AI professionally to be designated as a community. Community of practice traditionally works best for bridging gaps among incongruous actors. Boundary objects of material and the conceptual kind have played a role in creating harmonious work practices. Boundary spanners and relationships formed within the community can be instrumental in understanding the evolution of work practices. From boundary spanners' perspective, we can observe the softer emerging changes in their interactions and relations with others (Waardenburg & Huysman, 2022).

The nature of domain expertise has a higher role in forming a community of practice. Suppose experts mostly use formal and less substantive logic, and there is less uncertainty in finding solutions. In that case, experts may resolve to an aversion (Allen & Choudhury, 2022) or blind acceptance of algorithmic results. However, most of the expertise is built on years of situated, tacit and causal reasoning with values in the mix; the solutions are often uncertain and messy. In these scenarios, experts may want to rely on second opinions and knowledge from other domain experts (Lebovitz et al., 2021).

Another tension felt was in the daily work practices and workflow, where uncertainty over alarm standards was contested. Monitoring and repair depend on the correct diagnosis for the actions to follow. However, when standards are unclear, the workflow becomes ambiguous, and collaboration and cooperation among domain experts becomes estranged. This is detrimental to the transformation process with AI (Waardenburg & Huysman, 2022).

5.3 Limitations and future research

Our interpretive study has limitations. For studying AI systems in practice, our chosen methodology of an ethnographic field study is still ongoing. While we see our data as rich, five months is a relatively short time to capture the intended thickness of ethnographic data. However, the research data collection will continue over time, and the first author's efforts to become more embedded in the case will be intentional and engaged. Also, the study is based on a single Nordic renewal energy case organization and may have some limitations for generalizability.

Future research should extend beyond the specific context of renewal energy in the Nordic countries. Comparing and contrasting work practices and the tensions that arise during early human-AI collaboration will be of continued relevance across industries and countries. Future research may also pick up the theoretical and empirical reins for the subtle changes happening as part of DT, specifically around the softer attributes of DT, such as leadership, organizational culture, and work practices. We hypothesize that these small, more subtle changes, tensions, or disruptions are antecedents to more significant challenges and changes on the journey to human-AI collaboration.

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