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Cognitive technology development and end-user involvement in the Norwegian petroleum industry – Human factors missing or not?

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ABSTRACT

The petroleum industry is a high-hazard industry depending on reliable technical solutions. The industry tends to use increasingly advanced technologies including machine learning technology with increased difficulties for end users to keep abreast of how these technologies work. Thus, our research question was: How are end users involved in the development and implementation of cognitive technologies in the Norwegian petroleum industry to contribute to safe and reliable technical solutions? We used a qualitative explorative approach, with semi-structured interviews with 31 informants from 10 companies. Thematic analysis revealed the categories 'technology focus', 'understanding of end-user involvement versus end users' actual involvement', 'lack of access to end users', 'lack of human factors methods in early phases', and 'lack of official rules and regulations'. Findings show that during the earlier phases of designing algorithms and training data, end users are hardly involved. Regarding later phases with offshore testing, implementation, use, and improvement, end users are much more integrated in the process.

1. Introduction and background

Technological optimization and the automation of operations and maintenance are strategies used to increase efficiency, productivity, and safety in the offshore petroleum industry. Over the past decade, the development of advanced and complex technology designed to support or replace human tasks has increased and has thereby increased the safety and efficiency of operations and maintenance. For example, the aim of such technology can be to reduce the workload for control room operators by automating manual tasks that require high levels of concentration from operators (e.g., Anifowose et al., 2019; Chen et al., 2014; Hoske, 2021; Lordejani et al., 2018). Technology can also have faster response rates than humans, which can increase security and productivity (Mario et al., 2020; Sharma et al., 2015; Stephan, 2019).

To increase efficiency and maintain safety, developers need to know, during development, how increasingly advanced technologies will interact and function as part of existing sociotechnical systems (Leveson, 2012; Woods, 2016). Several authors find that the earlier the design stage in which human factors are considered, the greater the savings and influence on safety will be (e.g. Szymberski, 1997; RIF, 2019). Thus, for example, designers should consider ideally in the conceptual design phase which functions should be performed by humans and which by machines, and how this might need to vary with situation or context (e.g. Challenger et al., 2013; de Winter & Dodou, 2014). Developers need to consider early on how users will understand new technologies in the context of their work situation, what technological suggestions and actions are based on, and how the computer processes input variables (Bainbridge, 1983).

Challenges arising from the interplay between humans and technology, and their organization, must be understood and addressed to realize the potential advanced and complex technologies offer. If not, suboptimal technologies might be developed for operations in high-risk contexts, and in worst case, error traps. For example, one case in which the end users were not included in the early design phases led to the months-long evacuation and a shutdown in production of an oil and gas platform (Sætren et al., 2016). Ultimately, the designers could not fully understand how the technology would be used without understanding how the work was done, and the end users trusted the designers to understand their work environment and work processes (Sætren & Laumann, 2015). Extensive research has shown that to prevent such

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challenges, end users must be involved in the early phases of the design, development, and implementation of advanced technologies (e.g., Bennett & Flach, 2019; Carayon, 2006; Endsley, 2019; Gualtieri et al., 2005; Johnsen et al., 2017, Nemseth, 2004).

A rather recent technological development in this industry concerns cognitive technologies – programmed solutions and systems that are capable of collecting data through sensors, process this information, decide, and act and then learn from their performance in response to their actions (Walch, 2019). The types of tasks cognitive technologies can perform, or support, depend on the businesses in which they are deployed and the problems they are designed to solve. Many companies in the petroleum industry show great interest in cognitive technologies because they seemingly contribute to critical tasks being performed in a more efficient, reliable, or sustainable way (Gressgård et al., 2018; Johnsen et al., 2020). Nevertheless, as the petroleum industry is a high-hazard industry, there is an increasing need to understand the safety implications of cognitive technologies for the increasingly complex systems into which they are being introduced (Iversen et al., 2012; Woods, 1986).

Recent technological developments raise new issues concerning human operators working alongside cognitive technologies, or the development of operators' attention to or understanding of the technological suggestions or actions. As long as a human is left with the final responsibility in an operation, it is problematic if a cognitive technology's complexity removes from the human operator the ability to safely interact with the surrounding ecosystem (Woods et al., 2017). For instance, automated error-identification assistance has been found to decrease users' effectiveness in identifying and resolving errors in the system that the technology misses (Fleury et al., 2014). Cognitive technologies can never perfectly represent or be responsible for the dynamic ecologies in which they are situated; thus, humans with richer experiences of the surrounding systems are best placed to intervene and manage anomalies in those systems (Hoffman & Woods, 2011; Santio de Sio & van den Hoven, 2018). In designing safe systems, it is therefore essential to account for the effect of cognitive technology on human users' understanding of the 'ecology' being managed (Flach, 2017). Then, accepting that designers of cognitive technology are rarely, if ever, experts in the dynamic ecosystems in which the technology ultimately will be operated, it is essential that end users are involved in the design and iterative development of cognitive technologies (Norman, 1993).

In this study, we explored the specific development and implementation phases of cognitive technology. We investigated how companies integrate end users in the development and implementation of cognitive technology. We aimed to answer the research question: How are end users involved in the development and implementation of cognitive technologies in the Norwegian petroleum industry to contribute to safe and reliable technical solutions?

To answer this, the research analyses data from a study of how 10 companies integrate end users in the development and implementation of cognitive technology.

2. Theoretical framework

2.1. Cognitive technology

Rather than being interested in artificial general intelligence, companies are interested in new technologies that can improve operational efficiencies and/or safety by performing cognitive tasks that previously only humans could perform. Drawing on terminology from cognitive psychology, cognitive tasks can be said include elements of perceiving, learning, reasoning, planning and/or executing (Atkinson & Shiffrin, 1968; Reitman, 1965; Shannon & Weaver, 1963; Beetz et al., 2007). Because companies are interested in how technology can improve performance of definable cognitive tasks, the term *cognitive technology* is preferable to the broader term *artificial (general) intelligence* (Walch, 2019).

Automation and the technological optimization of operations and maintenance are seen as ways to increase productivity and safety in the petroleum industry (e.g., Chen, et al., 2014; Mario et al., 2020; Patro et al., 2021; Sharma et al., 2014). Technological possibilities have increased rapidly with increasing digitalization and data transfer capacities, making possible increasing combinations of sensors and computers (Hoske et al., 2021; Khosravanian & Aadnøy, 2021). Driven by the industry's need for efficiency and safety, these developments have led to increasing technological complexity in wells and on deck, large amounts of data, and reduced access to subject-matter experts (Chen et al., 2014). To realize automation and achieve technological optimization of the petroleum industry, there is a need for technology that can learn from experts to develop dynamic data models, which can then be used to process data from real-time sensor measurements and generate "expert" information or actions. Technology must also enable more efficient interactions between human decision makers and improve the capacity to source, analyze, and filter big data (Quesada, 2016).

Cognitive technology's processing capabilities lie in the data model, which can be viewed as analogous to the human brain (Atkinson & Shiffrin, 1968). A data model can be developed using theoretical knowledge and/or derived from data analysis (e.g., using machine learning algorithms). Experts understand how physics-based data models process input and provide output. Data-driven models, on the other hand, can be difficult to interpret but provide information about an operation that would be unavailable using physics-based modelling (e.g., because of a lack of sensors deep in the well). Combined, physics-based and data-driven data models provide a more comprehensive and nuanced depiction of the operation. This increased understanding of the operation enables sophisticated computer systems to carry out both advanced monitoring of the operation (perception and prediction) and the automation of operational processes (perception, prediction, and decision-making). The output of such technology derives from a seemingly higher cognitive function and is therefore called cognitive technology, a technology that can handle large amounts of data, either to support and improve human execution of tasks or perform tasks that previously required human operators (Wang et al., 2022).

Cognitive technology often learns from incoming data, captured by sensors or input by experts, to develop its own data model. This process is called machine learning (ML), and the model that is developed is called an ML model (Anifowose et al., 2019). Such data models can increase safety, for instance, by using a model to interpret signals from the well to determine whether they are early signs of uncontrolled kicks. Cognitive technology often performs tasks with human actors. Such collaboration can consist of cognitive technology using sensors to observe an operation in the field and presenting an image to one human actor who interprets it and decides what action to take based on the information provided. As cognitive technology becomes more sophisticated, the information presented to the human actor can become more elaborate. This can make it easier for the human actor to understand what is happening in the field but, at the same time, more difficult to see why and how the cognitive technology produces the information. Thus, it becomes more effective for technical actors to take over several human functions, such as understanding and deciding what happens in the field. Consequently, the human tasks are increasingly shifted to automated technical processes.

We define cognitive technology as follows: A technical system that (a) perceives (input), (b) calculates or processes, and (c) proposes or implements actions (output), where the calculation is based on ML models and people are aware and involved. Cognitive technology can perform three types of tasks: perception (e.g., well monitoring), prediction (e.g., predictive maintenance based on the comparison of historical data to real-time data), and planning (e.g., operational optimization, autonomous remotely operated vehicles [ROVs], or robots on deck). A cognitive system thus consists of several cognitive components, such as a cognitive technology and a human being (Woods &

Hollnagel, 2006). Additionally, a central aspect of a cognitive system is its ability to adapt to changes.

A limited number of cognitive technologies and ML models are used in the Norwegian offshore oil and gas industry. Most are in the concept development phase (Ernstsen et al., 2021). Consequently, operational experience with using ML models in the offshore petroleum industry is limited, and this was the focus of this study. To specify, this concerns offshore operations including maintenance, process, and drilling such as automated directional drilling, calculation of mud type and volume, early kick detection.

2.2. Human-centered design

A human-centered design is characterized by the focus on active and systematic interaction with end users and stakeholders during the entire process of designing and developing new technology (Pascal et al., 2013). Bringing the human in center is shown to provide higher productivity (Beuscart-Zéphir, 2007), improve user satisfaction (Vredenburg et al., 2002) and reduce costs, as making changes in a planning stage is less costly than making changes after producing and implementing technology.

In fact, several accidents have been partly attributed to poor human-centered design; for example, Boeing 737 Max Crash (Endsley 2019, NTSB, 2019), the Deepwater Horizon accident (National Commision, 2011), The Tesla accident (Banks et al., 2018), and the collision between Sjøborg supply ship and Statfjord A (Petroleumstilsynet, 2019). Cognition challenges were key in all these accidents. Correctly introducing human factors expertise into the design process of these systems could have prevented the accidents.

Not having the human in the centre for design could cause accidents as root causes for accidents are found to be related to design (Kinnersley & Roelen, 2007; Moura et al., 2016) For instance, Lootz et al. (2012) found that hydrocarbon leakage was due to design errors in 30–40% of the accidents from 2002 to 2009 on the Norweigan shelf. Thus, including human factors methods in design processes are of importance.

Human-centered design relies on the basic assumption that a socio-technical system (Trist & Baumfort, 1950) exists, with the social and technical aspects of work being symbiotic. Yet the term 'technical' is becoming increasingly broad with advances in computer science and information technology. This has led to a divided view of the 'cyber' aspect of human-centered design resulting in a cyber-socio-technical system (Patriarca et al., 2021), or a system in which cyber, social, and technical factors work together, as required in complex operations such as exploration and the production of oil and gas. This is a continuation of the traditional socio-technical system, with the intention of emphasizing the software part of the system. Although the technical components of the system have long been dependent on software, the increased use of ML models and autonomy makes it appropriate to have a framework where 'cyber' is emphasized. Regarding the cyber-social-technical perspective, implementing the cyber context within the phase in which human factors is included seems necessary for the safest possible development process.

As ML models increase in complexity, the potential arises for the black box dilemma to emerge (Zednic and Boelsen, 2021). ML models can yield accurate predictions without calculations being understandable to the user. The lack of understanding why a prediction has been made makes it difficult to improve performance, interpret the predictions, and identify why such a prediction has been made. It also makes it difficult to identify and quality assure against bias in the development of the ML model, called algorithmic bias. The black box problem occurs when an ML model's calculations, proposals, or implemented actions are difficult to explain, interpret, or understand. This often occurs when ML algorithms are trained and developed into advanced models and the end user is not involved in the design at an early stage.

Because the black box dilemma decreases the transparency of the decisions machines make, including end users in the earliest processes is considered even more important than previously. This is both for the end users to gain knowledge of how the machines they operate work and for the developers to gain knowledge about how the machines will be used. The relationship between ML model complexity and end-user requirements can be visualized in the matrix set out in Table 1.

2.3. Human factors methods and general technological development

The term "human factors in design" refers to how the design of technological systems and the work environment affects people's ability to perform safely and reliably, without endangering their health and well-being (Mc Leod, 2015). Another way to view human factors is to recognize their role in developing new systems that prioritize safety and usability (Boring & Bye, 2009). Selecting the best analysis method for a given project requires an understanding of the analysis's specific goals (Leonard, et al., 2004). Some human factors issues may only require basic methodological interventions, while more complex issues may require planning and preparation to determine which methods to combine. Technological development projects may need to go through multiple iterations of the method selection process (Stanton et al., 2013).

Previous studies have further found that human factors within technology development in the petroleum industry seem to be lacking in earlier development phases (Johnsen et al., 2017; Sætren et al., 2016). However, difficulties arise due to conflicts between demands driven by technology and the integration of human functions; for example, conflicts between human cognition and action capacities, and human operators' limitations and needs (Wilpert, 2005), and the variation in designers (Kim & Ruy, 2014). One way of dealing with this is to center the human rather than the algorithms in the design process (Schneiderman, 2020).

To ensure human reliability when designing technology in the oil, gas, and process industries, it is recommended to conduct human factors analyses (Jernæs et al., 2005; McLeod, 2015; Norsok, 2004; PSA, 2011). However, despite the importance of these analyses, reports indicate that they are typically conducted at a later phase in the process (Ernstsen et al., 2021; Jærnes et al., 2005). Technical safety is prioritized in technological development projects, and technical analyses are deemed essential, whereas analyses focused on human factors and human reliability are found not be considered natural part of risk analyses in the offshore oil and gas industry in the same way (Aas & Skramstad, 2010; Skogdalen & Vinnem, 2011; Sætren, et al., 2016; van de Merwe, Øie, & Gould, 2012).

There are many human factors methods that can be used to design new technology, depending on the specific goals, constraints, and context of the design project. Suggested human factors methods includes for instance task analysis (Kirwan & Ainsworth, 1992; Wickens et al., 2016) user-centered design (Begnum, 2021; ISO 9241), and human error analysis (Reason, 1990; Stanton et al., 2013).

Task analysis is a method that involves breaking down a complex task or activity into its component parts, with the goal of identifying the cognitive, physical, and environmental demands of the task. (Kirwan & Ainsworth, 1992; Wickens et al., 2016). User centered design is an approach that involves the active involvement of end-users in the design

Table 1
Development phases of ML models and recommended end user involvement.

	ML Development Phase	Implementation Phase
Interpretable machine learning (ML) models	The end user *can* be involved in the training of ML models.	The end user *must* be involved in the implementation phase.
Complex (black box) ML models	The end user *should* be involved in the training of ML models.	The end user *must* be involved in the implementation phase.

process. (Begnum, 2021; ISO 9241). Human error analysis is a method that involves identifying and analysing the types of errors that humans can make when interacting with the technology, with the goal of reducing the likelihood and impact of these errors. (Reason, 1990; Stanton et al., 2013).

Within petroleum industry, ISO 11064 has for many years been a common guideline. ISO 11064 is a set of international standards for the ergonomic design of control centers, such as command and control rooms, process control rooms, and emergency control centres. The ISO 11064 standard consists of four parts, which cover various aspects of control centre design and operation: ISO 11064–1 (2000): Principles for the design of control centres, ISO 11064–2 (2000): Layout and dimensions of workstations, ISO 11064–3 (1999): Ergonomic principles for the design of control centres – Control room layout, ISO 11064–4 (2013): Layout and dimensions of workstations for visual display terminals.

Regarding AI and ML and cognitive technology, we explore phases that are potentially carried out before the methods described in ISO11064 are employed. Programming algorithms are usually covered by programming methods instead of human factors methods. In our research it was investigated whether these methods should be better integrated.

3. Methods

We used a qualitative approach and an explorative design in this study. We conducted semi structured individual interviews and focus group interviews (Kvale, 1997; Brinkmann & Kvale, 2018) and based the analysis method on thematic analysis (Braun & Clarke, 2006; 2022).

3.1. Researchers

The researchers in this project have varied professional backgrounds. One holds a PhD in Psychology with a focus on safety in implementation processes of automated drilling technology in the Petroleum industry and has several years of research experience in the introduction of automated technology and human factors in the automotive industry. Another holds a PhD in Human Factors and has several years of experience as an engineer in the petroleum industry and research experience in cognitive technologies and ML. Furthermore, another holds a PhD in Biotechnology with in-depth expertise in the application of human factors and sociotechnical and cognitive systems in various transport industries. Another has a master's degree in organizational psychology and experience in human factors, with specialization in human–machine interaction (HMI). In addition, one has several years of experience in safety training and pedagogy in the petroleum industry, and holds a master's degree in pedagogy.

3.2. Context

In this project, the focus was on how end users in the sharp end are involved in the design, development, implementation, and use of cognitive technologies. Because of the broad variety of technologies being developed within the industry, we focused on various technologies based on what each company participants worked at and what the participants had experience with. The technologies revolved around the topics of maintenance, processes, and drilling on Norwegian offshore production platforms and the participants represented operator companies, contractors, and drilling companies.

3.3. Participants

The study included 31 participants who represented 10 companies within the oil and gas industry and companies involved in technology development for this sector. The participants interviewed had varied backgrounds: 14 were from operator companies, 12 from contractor companies, and five from drilling companies. Everyone was involved in one way or another in the design, development, introduction, or use of cognitive technology in the petroleum industry. Participants were chosen from a group of organizations the Petroleum Safety Authority Norway had selected based on their participation in technological development and on developing cognitive technology and operating in the sharp end with end users. Their roles spanned from managers and engineers to human factors experts and operators such as drillers.

3.4. Interviews

We conducted 15 semi structured interviews (Kvale, 1997), consisting of nine individual interviews and six focus group interviews. The interviews were conducted in the period August–September 2021 and lasted 45–60 min each. All interviews were conducted digitally due to COVID-19 restrictions and infection control. Present during the interviews were two to four researchers; one always had the main responsibility of taking notes, and the rest were either responsible for directing the interview or had the opportunity to formulate follow-up questions. Before the interviews, topics and examples of questions were sent to the participants. The interviews were not recorded due to recording not being approved by participants and Petroleum Safety Authority Norway. For this reason, no quotes are used in the result section as the data are based on notes rather than recordings. After each interview, the researchers who were present discussed the interview to summarize what was discussed. These conversations among the researchers were audio recorded, and the recordings were distributed to everyone on the research team.

Different interview guides were developed for respondents from operator companies, contractor companies, and subcontractor companies. The guides were based on various topics, including a description of the design and development process, how and when end users were involved, how procedures were developed, the training of end users, and how the end users understood how the technology worked and how it was designed. Questions included the following:

- 'Can you describe the development process?'
- 'What is your role in the design and development process?'
- 'How do you cooperate with the developers of the algorithms?'
- 'What competences do you demand from the developers?'
- 'Which tests (including technological and human factors) do you demand from the developers?'
- 'How well do you know the working conditions and work tasks of the end user?'

3.5. Analysis

We conducted a thematic analysis of the interview data with an inductive approach, based on reflexivity (Braun & Clarke, 2019). The concrete analysis was done by following the six steps developed by Braun and Clarke (2006). QSR NVivo (QSR NVivo, 2022) was used to organize the analysis of the written data into categories. The flexibility of the reflexive thematic analysis makes it suitable for analysing explorative qualitative research data. The themes were developed through coding the data based on subjective constructions, thus the researchers' background are relevant for the results. This is because the themes does not passively emerge from the dataset, yet themes are established through the interpretation of the researchers (APA 7, 2020; Braun & Clarke, 2019; Byrne, 2022; Elliot et al., 1999).

Reflexive thematic analysis consist of 6 phases (Braun & Clarke, 2006): 1) familiarizing with the data, 2) generating initial codes, 3) searching for themes, 4) reviewing themes, 5) defining and naming themes, and last 6) producing a scientific research report. According to the first phase, we conducted the interviews, took notes, and after all the interviews had been completed, we met to discuss the common themes, comparing notes, and identifying codes and categories. After this, we worked separately on further analysis. Thus, we familiarized ourselves with the data both individually and collectively. This was to get in depth knowledge of our dataset.

Second, we identified initial codes of the written material of the interviews according to phase 2 of conducting thematic analysis. Examples of codes from this phase were " competence demands from provider", "competence demands for end user", "framework for technology development", and "involvement of end users".

During this phase we also started an in-depth literature search based on the themes of cognitive technology, human factors, high-risk industries, and technology development processes. This resulted in the inclusion of theory based literature to the findings. During this step of the analysis, initial categories were established. However, the process of conducting reflexive thematic analysis is not linear and the process was thus conducted somewhat back and forth. For instance, one interview could have been preliminary coded before conducting the next in order to use the interviews to further elaborate on our previous findings.

The third phase consisted of organizing the data into meaningful groups, and themes were interpreted. Examples of themes were "understanding of the end user" "functionality for end user", and "change of work tasks".

In phase four, we were reviewing the themes, and ended up with the final ones. We discussed and agreed on these themes and defined what they mean based on the data to ensure that the analysis was based on empirical data from the interview notes. This process resulted in one overarching theme and four sub-themes presented in the result section. The flexibility of the method gives the researchers room for interpreting the levels of the themes depending on the content of the material rather than the quantity of the material (Braun & Clarke, 2022). During phase five, thick description were made in addition to grounding the themes to the data (Braun & Clarke, 2006; Braun & Clarke, 2022). The final phase was to write this paper.

3.6. Ethics

The topic of the project was not considered to be sensitive for the participants in any health matter or other matter such as racial or religious. The project was approved by the Norwegian Centre for Research Data (Sikt) to ensure the protection of participants' personal information.

4. Results

The findings show that there is a basic use of cognitive technology in the petroleum industry. However, there are several ongoing developments with the aim of advanced use of cognitive technology.

The findings show limited development of cognitive technologies in the petroleum industry and their limited use in operations. Additionally, if they are used, they are outside the loop of operations as standalone units that operators can choose to use or not. Even the most advanced technologies in operations and development are typically very advanced automated, physics-based deterministic technologies, and thus this is what the results are based on. The analysis resulted in the main category 'technology focus' and the subcategories 'perception of end user involvement versus actual involvement', 'lack of access to end users', 'lack of human factors methods for early phases', and 'lack of official rules and regulations'. These categories are factors that influence human centered design and end user involvement in technology development in Norwegian petroleum industry. This is presented in Table 2.

Table 2
Factors influencing human-centered design and end-user involvement in Norwegian petroleum industry.

Main Category	Subcategory	Explanation
Technology focus		No end-user involvement in initial development phases, which creates foundation of technological rather than human focus; input from end users does not affect basic design and development
	Perception of end-user involvement vs end-users' actual involvement	Perception existed that end users were heavily involved in development of new technology due to focus on training after technology was completed, importance ascribed to end users' comments on further development after using the technology, and including end users in process often referred to as a continuous improvement process Few participants reflected on that inclusion of end users were conducted in later rather than earlier development phases
	Lack of access to end users	End users' main task is to conduct operations, leading to a shortage of experienced end users as part of extensive technology development
	Lack of human factors methods in early phases	Focus on mathematicians in early phases of developing algorithms; developers lack access to proper human factors methods for including operators unskilled in this competence
	Lack of official rules and regulations	Rules and regulations do not exist for involving end users in earliest phases of technology development in Norway, but exist for later stages; creates the impression that inclusion is unnecessary for earlier phases

In the initial stages of integrating machine learning algorithms like the Random Forest into the field of cognitive technologies, a systematic process is followed. The first step involves clearly defining the specific task and goals of the cognitive technology application. Next, a comprehensive dataset is collected, containing relevant sensory inputs and measurements. This dataset undergoes preprocessing, which includes tasks like cleaning up data, reducing noise, and handling missing values. Afterward, the process of feature extraction and selection takes place to identify the key attributes that will be used as inputs for the chosen algorithm, whether it's the Random Forest or another suitable one. For supervised learning scenarios, the dataset is labelled to enable subsequent model training. The labelled dataset is then divided into training and validation/test subsets, forming a solid basis for training and evaluating the selected machine learning model within the context of cognitive technologies.

The initial technological development phases are characterized by development teams consisting of only people with a technological focus and no end users. Most participants reported that the earlier the developmental phase of the technology, the lower the chance that the person involved had been offshore or had an in-depth understanding of the working conditions of the end users for which they were designing the technology. For instance, one contractor depended on algorithms being developed in India for use in their technological solutions delivered to the Norwegian offshore petroleum industry. Additionally, by having only a technological focus in the initial phases, the development was found to be based on developing data models before finding out what the data model could solve.

4.1. Main category: technology focus

That the development process had a foundation based on a technology focus in the initial phases, influenced the contribution the end user could have. End users were hardly involved in initial development phases. End-user involvement in later phases meant, that the input from end users influenced only later phases and not early settings of functionality. The reasons developers did not focus on human operators in early phases were found to be (a) the perceptions of end-user involvement versus end users' actual involvement, (b) a lack of human factors methods in early phases, (c) a lack of access to end users, and (d) a lack of official rules and regulations.

4.1.1. Subcategory 1: perception of end-user involvement versus end users' actual involvement

The participants were confident that a great degree of end-user involvement already existed. This was the case for both developers and end users such as drillers who we interviewed. The respondents mentioned three key focus areas:

- Training and allowing end users to take part in learning how to use the technology before implementation by using simulators.
- Allowing end users to have a say in how the technology should look; many participants emphasized the presentation of workshops during the development processes, including sections on HMI.
- Including end users in the continuous improvement process by encouraging them to provide feedback for adjustments after the technology has been implemented and used.

However, the findings show significant variance in end users' degrees of participation throughout technology development. The inclusion of end users did to a large degree increase as the development process approached completion. During the earliest phases, during the development of algorithms and planning, most did not consider including any end users. Only one developer regularly included end users during these phases as well, using the interactive machine learning (IML) method to enable participants with different skills and competences to understand each other.

4.1.2. Subcategory 2: lack of access to end users

There are not sufficient experienced end-users available for technological development processes. Many technologies need to be developed, and many contractors and subcontractors are involved in such processes. When developers demand the inclusion of end users in their development processes, the developers often focus on including experienced end users in the process. However, experienced end users are not accessible to the degree that the technology development market seems to need.

The end users' main task is to operate the technologies. Most end users do not have the training and education required for them to participate in technology development. Furthermore, technology development has to a certain degree reduced the number of end users, giving rise to the question of whether end users should be used for operations or all levels of technology development. Another reason for the lack of experienced end users is that the technology being developed demands such future competencies that the end users do not exist today. Finally, the analysis revealed that accessibility to end users also depends on whether the company developing the technology has the authority to demand the inclusion of end users because they own the platform or have end users as staff, or whether they are a smaller subcontractor without such access to end users.

4.2. Subcategory 3: lack of human factors methods in early phases

Participants held a common understanding that it is challenging to involve end users in the earliest phases of development because the competence and skills of the mathematicians creating the algorithms and the end users in the drilling cabin were so different that they would have problems understanding each other. They argued that including end users in earlier phases of development would increase the risk of human error and incorrect programming due to a lack of understanding of the programmers' work. Nevertheless, when asked which human factors methods were used throughout the development phases, most participants did not name any specific methods used, an only one mentioned IML method as previously mentioned.

4.2.1. Subcategory 4: lack of official rules and regulations

No rules and regulations govern involving end users during the earliest phases of technology development of algorithms in ML in Norway, was mentioned by the participants. Thus, the industry seems to interpret this as there being no need to involve end users in these phases. The industry seems to be waiting for the authorities and the authorities for the industry to develop best practices on the inclusion of end users in the earliest phases of even more complex technological solutions and ML in the future. Several participants mention human factors methods specifically articulated and easy to access, such as ISO-11064, regarding end-user inclusion in later phases.

5. Discussion

Regulations have been implemented regarding increased user involvement in the development and implementation of technologies in high-risk environments, and recommended standards such as ISO 11064 on designing control rooms, provide useful insight on how to achieve this. However, the growing of technology that increasingly learns by itself and makes its own decisions gives rise to key questions: How well would the end user understand how the technology works, and how should the end user be a part of the development process? Therefore, the research question was: How are end users involved in the development and implementation of cognitive technologies in the Norwegian petroleum industry to contribute to safe and reliable technical solutions? Our study resulted in one main category, 'technology focus', and the subcategories 'perception of end-user involvement versus end users' actual involvement', 'access to end users', 'lack of human factors methods in early phases', and 'lack of official rules and regulations'.

For long-term efficiency, maximum safety, usability and other gains, it is often claimed that end users should be involved early in the development and implementation of cognitive technology (e.g. Driscoll et al., 2008). This claim is supported by extensive research in various disciplines such as human factors and meaningful human control (Nemseth, 2004), sociotechnical systems (Carayon, 2006), cognitive systems (Gualtieri et al., 2005), and HMI (Bennett et al., 2019; Sætren et al., 2016). Nevertheless, computer engineers and system developers in various industries still produce designs that are more technology centric than user centric (Challenger et al., 2013; Woods et al., 2016), a view supported by our findings. In general, our findings show that user involvement increases only during later development and implementation phases of technology in the Norwegian petroleum industry. Including human factors expertise throughout the design phase, also in the earliest phases of design of algorithms, might thus be beneficial. This is because machines learning models should have input by humans with domain expertise to consider the quality and relevance of input data, understanding the assumptions for the models as well as the interpretation of the model training data (Endsely, 2023). The task of a human factors expert could be to ensure presence of end users and function as an interpreter finding ways to increase understanding between a data programmer and operational end users. Bringing in expertise on human factors methods would increase a human centered design process as they would understand how to focus on identifying end users' needs and how to use the end users input in the design. Additionally, there is an intensifying need in the petroleum industry to obtain oil and gas from areas that are harsher and harder to reach, which results in the prioritization of the development of increasingly advanced technological solutions. Even though the scientific literature recommends user involvement from earlier phases, our findings show that, in practice, this does not occur.

First, there was a perception that end users were very much included in the development process. Regarding later development phases, this is correct, with simulator training, workshops, HMI design, and so forth. However, for earlier phases, including the development of algorithms, end users are absent. This perception of participation might give end users a sense of trust in the development process. The findings therefore shows a difference between work as imagined and work as done (Hollnagel, 2017).

End users' trust could also be based on other factors (Sætren et al., 2015), such as confidence in the mathematicians who develop algorithms, because the end user lacks the competence to understand the process. This may mean that trust is based on an inadequate understanding of the complexity of technology and an acceptable norm. From a psychological perspective, thus, trust can be a substitute for understanding that makes end users accept something that they would not have accepted if they had fully understood the complexity and risk (Torbiörn, 2006).

The organizational and human challenges posed by cognitive technology are particularly demanding. Most human operators have so far had a basic understanding of how the technology they use works, but the computer models that enable technology to perform cognitive tasks can become so complex that people have difficulty understanding it (Bainbridge, 1983). This is problematic as long as human operators have the ultimate responsibility for safety–critical operations (Santio de Sio & van den Hoven, 2018).

Second, there is a shortage of end users for handling the demands of both working in operations and working in technology development. One solution could be to spread the competences, and limit involvement in later phases and use these resources in earlier phases. However, this might demand changes to rules and regulations.

Third, there seems to be a lack of well-designed human factors methods to use in the early phases of the development of algorithms for high-risk industries. Some methods exist, such as interactive machine learning (IML) (Ware et al., 2001). Even though this method is designed for commercial development and not validated for technology used in high-risk operations, it could, for instance, be used as the basis for further method development for advanced cognitive technologies. The developer must understand how the end user interacts with cognitive technology so that they can form effective situational awareness and manage risks when critical situations arise (Hoffman et al., 2018). They also need to understand how cognitive technology can generate data that is interpreted differently depending on the user and situation (Carayon, 2005).

According to the findings, one reason the industry does not involve end users in the initial phases is that misunderstandings could increase the risk for human error among mathematicians if end users are involved because end users lack the competence for this design phase. However, this could be an argument for the opposite too, as the mathematicians, sometimes situated in other countries such as India, which was mentioned, do not understand the contextual factors related to the work environment of end users in the Norwegian petroleum industry. This is a reason the inclusion of human factors is recommended in the earliest phases (Sætren et al., 2016).

Moreover, how humans and cognitive technologies can work together to achieve the 'cognitive flow' necessary for successful management of processes in both routine and critical situations has been questioned (Hollnagel et al., 2006). Santio de Sio and van der Hoven (2018) pointed out, among other things, that cognitive technology must always support people and that people in cognitive systems must always understand situations so that quick decisions can be made to avoid unwanted and critical events.

Fourth, official rules and regulations are lacking for developing algorithms. Even though there are regulations governing participation in matters of importance for the working environment or that employees shall contribute in the establishment, follow-up and further development of management systems (Norwegian Framework Regulations §13; §17; Working Environment Act), including change processes (Levin et al., 2012) and thus could be interpretated to include technological development, it does not occur for developing specific smaller parts of larger technological systems or algorithms in particular for ML. Our findings show that as long as the interpretation from responsible for design processes are that there are no specific rules and regulations exist regarding the earliest design phases, the industry will not include end users in these phases. As cognitive technology develops so that it can take over more of the operational and tactical responsibility than it manages today, new demands are placed on the interaction between person and cognitive technology. Operational and tactical responsibility is about performing the operation in addition to monitoring and adapting immediate changes in and around the operation. The new requirements that must be set are technical, to address the lack of data transfer capacity; organizational, to develop precise industry standards; and based on a people-centered perspective of cognitive technology in the petroleum industry to facilitate the interaction between humans and cognitive technology (Carayon, 2006).

In interpreting these findings, the reader should bear in mind that the study is solely qualitative and limited to the petroleum industry in a single country. The ability to generalize across situations other than those studied here is therefore limited. Otherwise, the validity of our study can be described in terms of five factors that build trustworthiness (Hayashi et al., 2019): 1) The researchers focused intently on the study during the study period, and they were all part of the process from the planning until completion of the project. 2) Data was organized based on a deepening the understanding of the topic and based on well-established methods. 3) Data coding was structured systematically using thematic analysis of detailed notes taken by a dedicated scribe. 4) By including a variety of organizations and levels in the supply chain of technology development, we ensured the inclusion of several sources of data; all researchers took part in analyzing and interpreting the data, ensuring a broad view of the data collected. 5) Throughout the discussion section, the study findings are discussed according to the theoretical framework presented in the paper.

6. Conclusion

Based on the research question – How are end users involved in the development and implementation of cognitive technologies in the Norwegian petroleum industry to contribute to safe and reliable technical solutions? - this study found that user involvement increases during the development and implementation phases. During the earlier phases of designing algorithms and training data, end users are hardly involved.

Regarding later phases including testing and implementation offshore, and the use and improvement phases, the end users are integrated in the technological development process. The findings suggest that end users are more available during this phase, there are human factors methods available, and there are official rules and regulations that promote participation during testing and implementation. Including end users in as early phases as developing algorithms for ML technology, could be a beneficial contribution to safe and reliable technical solution. Such inclusion could for instance increase users' understanding of the systems' decisions and actions, gain a more optimal distributed situation awareness, and have a more correct degree of trust towards the technology.

Within the Petroleum industry and beyond, the understanding of the functions of human operator and technological operator is an implication found. We propose re-evaluating the human operator's strengths and weaknesses relative to their computer counterpart when it comes to allocating functional responsibilities. Traditionally, system designers have recognized the human operator being stronger in creative responsibilities, whereas they reserved what earlier used to be manual tasks, for the computer. With the advance of cognitive technology, computer agents can perceive and generate insight about what is happening and predict more about what will happen. For some operations, designers should consider assigning the computer rather than the human operator novel decision-making tasks when designing the system. This re-evaluation can have implications for design standards that appreciate the human operator as the only creative agent.

The petroleum industry has not implemented complex ML models in their operations. However, the technology develops rapidly, and operators are deeply involved in comprehensive research and development projects that aims at using the capacity of ML models to carry out safer and more efficient operations. As seen in other domains, there could be a higher risk of accidents when rules and legislation do not keep up with technological development.

There are regulations covering development work. The interpretation of this seems to be an assumption that this might not be covering development of every component of a technology such as the earliest stages of cognitive technologies and development of algorithms. Due to the novelty of the research area, further exploration regarding if and how the framework regulation fits developing algorithms for ML technology, seems important.

Consequences on performance due to insufficient human factors methods during development phases, could be that the design is not suited for the actual operation and that it could become a human error trap. Additionally, the situation awareness for the operator could be limited and decisions made on a misunderstanding. If the operator does not understand how the technology makes decisions, the operator might not know how to respond to its actions optimally.

The current research could drive the development of well-suited human factors methods for the early phases of advanced algorithm development in the petroleum industry. There is need for further research on this theme, including developing new human factors methods for earlier development phases, evolving existing human factors methods for earlier phases, and exploring how to use end users' competences optimally during development processes, as the latter is considered a scarce resource. Although researchers argue for the early involvement of end users, developers seem to have a different idea of what end-user involvement means. While a failure to involve end users early on in true design and development activities could be due to the increasing scarcity of end users, as our study implies, it could also be due to a lack of readily available empirical evidence of the effects of failing to involve end users. Such evidence is needed to convince managers investing in cognitive technologies of the long-term benefits of involving end users as 'designers' – and the potentially catastrophic consequences of not doing so. Comparative evaluations of attempts at ecological versus more traditional human–machine interface design could also convince managers of the value of early end-user involvement.

Moreover, it is also important to further examine the optimization of the design processes of algorithms for equipment used in high-risk operations for end users. Additionally, there is a need to develop appropriate rules and regulations and involvement from the authorities, which need further research.

Statements of declaration

This manuscript has neither been published before nor is being considered for publication elsewhere. All authors have read and agreed to the submission of the paper to the target journal.

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Author contribution

Dr. Gunhild B. Sætren has had a role contributing in all parts of the project including conceptualization, funding acquisition, data curation, writing – original draft, writing – review & editing, visualisation, investigation, validation, formal analysis, methodology, and resources. She was responsible for the publication process of the article.

Dr. Jørgen Ernstsen has had a role of project manager and partook in the research process including conceptualization, funding acquisition, data curation, writing – original draft, writing – review & editing, visualisation, investigation, and project administration.

Dr. Ross Phillips has contributed in the research project including conceptualization, funding acquisition, data curation, writing – original draft, writing – review & editing, investigation, and validation.

Eir G. Aulie has contributed with conceptualization, funding acquisition, data curation, writing – original draft and project administration.

Hege C. Stenhammer has contributed with conceptualization, funding acquisition, data curation, writing – original draft.

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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