EXplainable AI Interfaces with (and for) Expert Operators: A Participatory Design Approach

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eXplainable AI Interfaces With (and for) Expert Operators: A Participatory Design Approach

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Abstract

This paper explores the integration of user-centered participatory design (PD) methodologies to develop feedback solutions within eXplainable AI (XAI) systems applied to time-series data in industrial contexts. Through this research, we have found that user-centered PD methodologies are important inclusions in designing feedback solutions for highly technical and complex industrial processes with XAI systems working with time-series data. By involving expert operators from the Kraft process in every step of the design process, we ensured that the feedback solutions were tailored to their specific needs, enhancing usability and relevance. Key recommendations include the need for immediate usable insights, model selection to enhance trust, quick and easy feedback interactions, and efficient interaction modalities. Our findings demonstrate the value of user-centered PD in minimizing unwanted features and aligning the design with industrial requirements. The insights gained offer a foundation for future research to adapt these recommendations to other industrial settings, contributing to the broader application of effective XAI interfaces and feedback solutions.

CCS Concepts

• **Human-centered computing → HCI design and evaluation methods**.

Keywords

Explainable Artificial Intelligence, XAI, Industry 4.0, Feedback, Design Recommendations, Human-AI Interaction, User-Centered Design, Participatory Design.

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1 Introduction

The adoption rate for industrial Artificial Intelligence (AI) solutions is particularly low due to their oftentimes opaque nature [6]. Requirements for AI applied in industry differ significantly compared to requirements identified in consumer-oriented applications [28]. For instance, in the process industry, which is the context of this research, the users are usually domain experts who are highly familiar with the complex systems used in their workspace. In this context, as it affects production quality and efficacy, successful industrial AI applications rely on transparency and understandability [42]. EXplainable Artificial Intelligence (XAI), which is traditionally a computer science-driven field, has increasingly opened up to interdisciplinary researchers as there is a need to cater the systems to all kinds of users [1], to ensure that they are more transparent, interpretable, and trustworthy [60]. However, due to the high level of complexity in the process industry, the success of AI is not only dependent on explainable interfaces but also a rather novel notion, that the operators monitoring the process can provide feedback to and interact with the AI to improve it. Due to the complexity of industrial processes, and the difficulty in obtaining labeled training data with adequate variance for producing highly accurate AI models, the models need to be receptive to operator feedback to guide their improvement. Previous research shows that there is a need for

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features that enable users to give feedback to AI systems [37, 66, 74], and there are some suggestions on how to implement such features [63, 65, 66]. There is, however, to the best of our knowledge, a lack of research examining how such feedback solutions can be designed for the industrial processes, to properly align with the specific needs of particular expert operators. As a prerequisite for feedback, a well-adjusted XAI interface is necessary to enable the human-in-the-loop scenario [65]. This necessitates that developers and designers have an in-depth understanding of the decision-making process of the operators, the use of explanations, and their explanation needs [24, 46]. Similarly, enabling users to provide feedback to these systems requires the same domain-specific understanding. To achieve this in highly technical and complex industrial contexts with particular expert users, we employ Participatory Design (PD) [59, 64] to ensure a User-Centered Design (UCD) [16]. To the best of our knowledge, this has not been done before in the context of an industrial process. In this research, we contribute the following to the HCI community:

(1) This research outlines a user-centered PD approach for developing feedback solutions within XAI interfaces. These aim to support long-term usage in an industrial setting and should provide the operators with tools to improve the prediction capabilities of the underlying AI over time. To the best of our knowledge, this is the first study to apply user-centered PD for this topic in the context of the process industry.
(2) Through user-centered PD, a set of design recommendations are derived that can support the development of feedback solutions and their long-term usage within XAI interfaces in industrial processes.

2 Related Work

2.1 AI in the Process Industry

The adoption of Industry 4.0 has taken use of various technologies such as IoT [49], cloud computing [31], system integration [15] and simulation [21], in turn leading to an increased interest in utilizing AI in process industries due to benefits such as higher consistency in product quality coupled with lower operational costs while providing flexibility and scalability to organizations [28, 70]. As such, AI has been introduced in various contexts such as smart manufacturing [22, 55, 69], predictive maintenance [27, 36, 50], and cybersecurity [13].

Typically in the creation of Machine Learning (ML) models for industrial contexts, domain experts are only involved in the requirement elicitation and data labeling phases, while being left out in the evaluation phase of the model [68]. However, to succeed in implementing AI applications in industry, the AI systems need to be human-centered and continually open to domain expert feedback to address the challenges and requirements of industrial processes [71]. We extend the work here by introducing a user-centered PD process to allow us to integrate expert operators in defining feedback interactions with an XAI system in industrial processes.

2.2 Explainable AI (XAI)

In contrast to interpretability, which refers to the extent to which a model is understandable to an observer, explainability refers to an inherent property of a model that gives insight into its inner workings [4]. In domains such as process industries where the impact of decisions might bring great consequences, the explainability of models becomes crucial for getting insight into potential reasons for a model's output. XAI methods and visualizations have been explored in contexts such as medicine [10], welfare screening [76], and closer related to process industries such as machine life estimation [61], manufacturing fault detection [30, 43], predictive analytics [34], and anomaly detection [41]. However, the existing body of XAI research is largely skewed towards classification models using image data, in turn leaving XAI methods for regression tasks using time-series data an underrepresented field for research [48].

Explanations can be divided into two general categories: *global explanations*, which cover the extensive logic of a model, and *local explanations*, which refer to the reasons for a model to make single decisions in particular situations, such as one particular forecast at one point in time [23]. Ribera et al. [57] attempted to address a user-centered workflow for XAI, where they proposed that local explanations are most suited for domain experts such as control room operators, leaving global explainers for developers or AI researchers. As such, not only should the XAI methods focus on explaining instances of single model outputs for control room operators, but the feedback provided by these users should also revolve around model outputs rather than the inner workings of models.

Moreover, in industrial applications, visualization mechanisms for explanations are preferred since traditional non-visual explanations are deemed insufficient. According to Kovalerchuk et al. [32] visual and granular methods of explainability increase both the validity and interpretability of AI models, with the supporting argument being that visualizations are more appealing to human perception. Visual explanations also offer more domain-specific implementations where the design of interfaces varies depending on the specific explanatory needs of each domain.

Thus, in this work we extend on the limited research that has been presented in the domain of XAI in industrial processes, by introducing a user-centered PD approach to include expert operators in defining feedback interactions with an XAI system. As a result of this approach, we designed a visual XAI interface that supports feedback interactions.

3 Pulp Production Process Operators

In this paper, we address the development of feedback interactions for an XAI system in an industrial process by deploying a user-centered PD approach in a Pulp Production Process. In this section, we outline a description of this process and describe the expert operators that support it.

Process industries refer to plants running a continuous process of turning one material into another, often refining it through various discrete steps. One such process, which has been the context and focus of this work, is the Kraft process to produce paper pulp. A central component of the Kraft process is delignification, where wood fibers are separated by gradual removal of lignin [2]. Utilizing a thermo-chemical conversion process, sufficient lignin can be removed from the pulp to obtain the right properties for the intended quality of the final product. A central term in this process is Kappa,

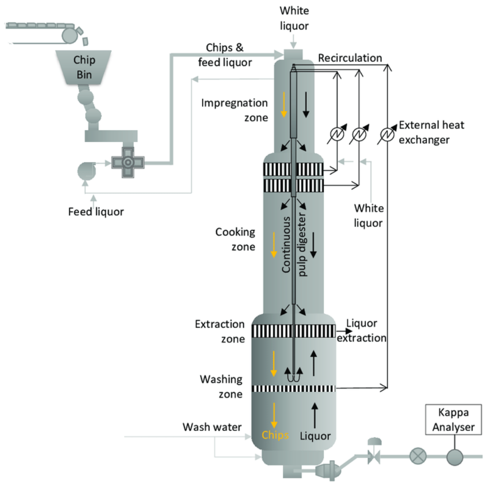

Figure 1: A schematic of a digester carrying out delignification, created by [54].

which refers to the amount of remaining lignin in the pulp leaving the conversion process. A schematic of the process can be seen in Fig. 1. Maintaining a sufficient Kappa is one of the main priorities of the control room operators driving the process. However, as the conversion process depends on a prolonged chemical reaction, the effects of operators' adjustments are typically delayed multiple hours, in turn increasing the need for proactive decision support in terms of a multi-hour forecast by a regression model and associated XAI methods. In this particular context, the operators work in a centralized control room with many computer screens on which they monitor the ongoing process. In this research, we outline through user-centered PD how expert operators can provide feedback to and support an XAI system aimed at producing a prediction for the Kappa.

4 Methods and Process

The main objective of this research is to develop feedback solutions for an XAI interface in an industrial process, such as the Pulp Production Process, through a user-centered PD approach. Therefore, we employ an iterative design process [75] that incorporates the expert operators of the Pulp Production Process in each iteration. The three main phases are: (1) Expert interviews to ground the problem space and understand the expert users. (2) A PD workshop aimed at developing feedback interactions together with the expert operators. (3) Expert operator evaluations of the prototypes followed by final iterations of the feedback solutions within the XAI interface.

4.1 Ethical Considerations

During all activities with participants, we provided them with consent forms, exercised caution in handling personal data, prioritized privacy, and complied with ethical standards and regulations throughout the process. All collected data throughout this research has been anonymized to ensure the privacy of the participants. The development of solutions for deployed XAI systems required a keen focus on safety, emphasizing clear communication between humans and machines to mitigate potential hazards in the production process where the XAI systems are used.

5 Phase One: Expert Interviews

Through expert interviews with the operators, we aimed to gain insight into the process they work with, how they relate to the usage of XAI in their workspace, and an exploration into how they would wish to interact with such a system. The interviews were divided into four parts, focusing on different areas of importance:

(1) The first part aimed to understand the operators' work environment and tasks, including their daily routines, break times, process workflows, computer systems used, and the benefits or drawbacks of these systems.
(2) The second part focused on motivation, using Ryan & Deci's theory [58] to determine whether operators were influenced more by intrinsic or extrinsic factors. Questions addressed work challenges, opportunities for improvement, the use of computer system features, and aspects of their work they found meaningful.
(3) The third part centered on feedback. The questions were grounded using theoretical approaches to XAI and utilized the connection between XAI and social sciences according to Miller [45], to create questions aimed at eliciting feedback requirements via the operators' interactions with colleagues. The questions aimed to understand how operators give and receive feedback from colleagues, learn from each other, and the challenges of providing feedback. Additionally, the operators were asked about their perspectives on giving feedback to digital systems.
(4) The fourth part examined the operators' AI experience, specifically their use of a previously unsuccessful XAI interface with a feedback feature. These questions were therefore aimed at understanding their experience of that implementation, what they thought of it, why or why not it was successful, and their impressions of giving feedback to that system.

5.1 Participants

In total, five operators were interviewed. Four participants were between the ages of 30 and 39 years old and one was between 18 and 29 years old. All the participants were men, had varying degrees of education, worked as process operators, and had varying years of experience in their current positions. For the full demographic information, see Table 1. While the number of expert users is low, we believe it is sufficient as the goal of the interviews was not to gain a wide range of insights, but rather a deeper understanding of their experiences [11]. Several studies have been successfully carried out with a small number of expert users (5-10 people) [40, 52, 62] and thus we argue that the low amount of expert users does not affect the quality of the results.

5.2 Procedure

The participants were given a consent form upon the start of the interview. After this, they received a paper where they filled out demographic information. The interviews were semi-structured, meaning that we asked questions outside of the interview protocol

Participant	Age	Gender	Education	Job	Experience
P1	18-29	Male	Technical college engineer	Operator	7-10 years
P2	30-39	Male	High school	Operator	1-3 years
P3	30-39	Male	Higher vocational education	Operator	4-6 years
P4	30-39	Male	4-year high school	Operator	11+ years
P5	30-39	Male	4-year high school	Operator	7-10 years

Table 1: Expert interview participants' demographic information.

when deemed necessary. The interviews were recorded with offline recording equipment and were conducted with five operators inside the control room of a paper mill. The interviews lasted between 30-40 minutes, they were conducted in Swedish and only the quotes presented in this paper were translated into English. The interview data was then transcribed and prepared for a thematic analysis, as described in the following section.

5.3 Analysis

For the analysis, the six steps of thematic analysis defined by Braun & Clarke [8] were followed. The process began with transcribing the audio data from the interviews to ensure familiarity. The software MAXQDA 2020 [67] was utilized to analyze the data and identify codes and themes. The first interview was coded in collaboration between the first two authors to ensure alignment in code selection. Then the remaining four interviews were coded separately. Codes were selected based on the interview questions (deductive codes), and additional codes were added as they emerged from the interviews (inductive codes). Some quotes were coded multiple times as they fit into multiple different codes.

The result of the thematic analysis is presented in Fig. 2. Briefly summarized, the initial field study results reveal that effective communication between operators and AI systems is crucial, emphasizing clear, concise, and continuous exchanges that facilitate easy feedback. Operators desire interaction and collaboration similar to human-to-human interaction but without social sensitivity, which helps build trust and keeps them motivated. Trust is essential for successful adoption, and transparent communication is needed to demonstrate the AI's learning and improvement. Furthermore, the operators are driven by both intrinsic and extrinsic motivations, including innovation and product quality, and their willingness to provide feedback is highly dependent on seeing tangible impacts from their input. The interconnected themes of communication, trust, and motivation highlight the need for a holistic approach to implementing feedback features.

The following sections are dedicated to more detailed results gained from the initial field study. In Figure 2, the circles represent the themes and the rectangles represent the sub-themes. The lines represent the connections between the themes and sub-themes. Four major themes emerged as a result of the thematic analysis. The following describes the connections between themes and sub-themes to each other in more detail:

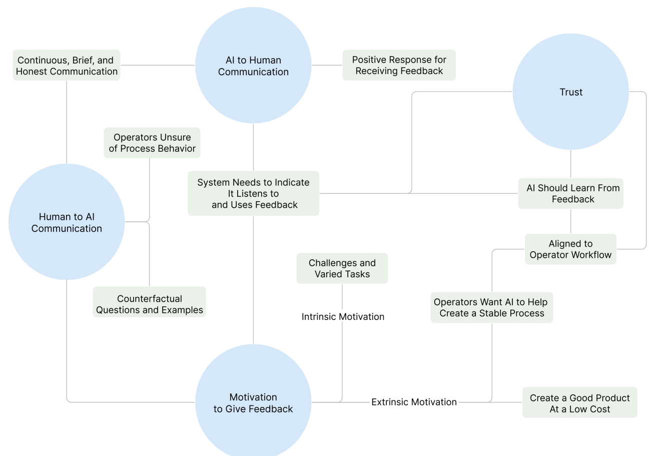

Figure 2: Figure representing the results of the thematic analysis of the expert interviews.

5.4 Phase One Findings

Human to AI Communication: This theme highlights key considerations for how operators wish to interact with AI, touching on preferred communication methods and challenges in discussing the process in general as it is very difficult to predict. As seen in the connected sub-themes, operators prefer brief, direct, and continuous communication, noting that while human-to-human interactions require social sensitivity, human-to-AI communication should be straightforward. They believe interactions with the AI should resemble human interactions without the need for social nuances, as one operator expressed:

[...] if you can give it almost the same way as you can give it to a colleague, then it can be quite fun [...] (P2)

Using familiar, clear, and concise communication can increase operators' motivation to give feedback.

AI to Human Communication: Similarly to how operators interact with the AI, there are important considerations for how the AI system interacts with the operators. This theme and the *Human to AI Communication* theme share the sub-theme of *Continuous, Brief, and Honest Communication*, which is crucial for successful interactions. The AI needs to communicate in an understandable and time-efficient manner, as operators do not want to spend excessive time interacting with it. One operator suggested:

The system should maybe ask a counter question and say ... or give a suggestion of something to do instead, [...]. (P1)

This reflects the collaborative communication style among operators, who often discuss to determine the best course of action, as emphasized by another operator:

I expect that we should try to agree on a way forward. If my idea is better, or this person's idea is better. It is oftentimes very difficult to know and so we need to communicate [...] (P5)

For effective AI-human communication, the system must show that it listens to and uses feedback provided by the operators, thus feeding into their intrinsic motivation and increasing trust as the AI shows improvement over time.

Trust: As shown in Fig. 2, *trust* is crucial for *AI to human communication*. Successful interactions between the AI and operators depend on the operators' trust in the AI. One operator highlighted this, stating:

You want to trust it. Because if we are to follow it all the way (the AI's recommendations), then we should do that and you should be able to trust it. (P4)

Trust is essential for XAI systems to succeed; the AI must align with the operators' workflow and demonstrate continuous improvement. Effective communication showing that the AI learns from operator feedback is vital to maintaining their motivation to use the system.

Motivation to Give Feedback: Several factors influence operators' motivation to give feedback, which is central and interconnected in the thematic analysis (Fig. 2). The motivation to give feedback greatly depends on the other three themes. Firstly, operators need to know that their feedback is actively used by the AI; failure to indicate how feedback is received and utilized negatively impacts motivation. Secondly, feedback interactions should be continuous, brief, and honest to avoid being time-consuming and monotonous. Thirdly, trust in the AI is crucial, as operators are more motivated to give feedback if they believe the AI improves due to their input. Lastly, operators are driven by the goal of creating a good product at a low cost, with a stable and manageable process, which enhances their intrinsic motivation to provide feedback. This demonstrates a pre-existing baseline of motivation for the usage of AI within their industrial context. One operator stated:

[...] a lot of the people I talk to here think that AI is the next big thing. So I think there are a lot of people who are motivated to help to see how good it can be. Because it could offload a lot in stressful situations or in potentially dangerous situations where you work with high pressure and temperatures. (P3)

Gradually improving the AI is in the best interest of the operators. However, this baseline of motivation is only as useful as the model itself, since the operators lose motivation to provide feedback if the AI fails to be useful or to acknowledge and use their inputs.

6 Phase Two: Participatory Design Workshop

Based on the findings from Phase One, we created low-fidelity prototypes of feedback solutions used in the PD workshop (a selection of these can be seen in Fig. 3, 5, 4, and 6). To the best of our ability, we aligned the feedback solutions with the desires of the operators found in Phase One (see Fig 2).

This session aimed to understand the operators' preferred feedback features for the XAI predictions by letting them choose designs and alter them to address their preferences. Based on literature arguing that gamified features increase acceptance and usage of novel technologies [12, 14, 72], we also introduced ideas for gamified scoring systems and AI improvement statistics, hoping to understand if such features contribute to long-term usage in this context.

6.1 Participants

Six operators were part of this workshop, two female and four male. Three participants were between 18 and 29 years old, two were between 30 and 39, and one was between 40 and 49. They had varying degrees of education and two participants had worked in their current role for one to three years, one had worked for four to six, two had worked for seven to ten, and one had worked for eleven or more. For full demographic information, see Table 2.

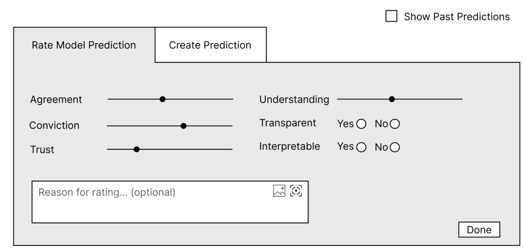

Figure 3: One alternative to the *Rate Model Prediction* feedback view.

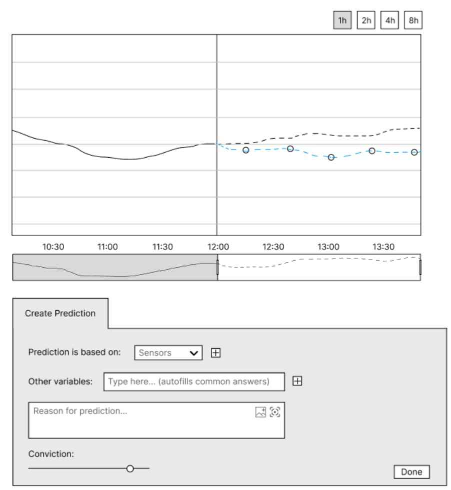

Figure 4: *Create Prediction* view with an interactive graph where the operators can create their own prediction coupled with a feedback window where the operators get to select what sensors the prediction is based on.

6.2 Procedure

We conducted three sessions with a total of six operators of the pulp production process. Each individual session consisted of two operators and two designers (two of the authors of this paper). The operators each filled out a consent form and the session was recorded capturing both video and audio. The session began with a short introduction mentioning the results from Phase One (Section 5), allowing the operators to get into the mindset that any feedback interaction should support long-term usage. Following this,

Participant	Age	Gender	Education	Job	Experience
O1	30-39	Female	Higher vocational education	Operator	1-3 years
O2	18-29	Female	High school	Operator	1-3 years
O3	18-29	Male	Higher vocational education	Operator	7-10 years
O4	40-49	Male	High school	Operator	11+ years
O5	30-39	Male	Higher vocational education	Operator	4-6 years
O6	18-29	Male	Technical college engineer	Operator	7-10 years

Table 2: Operators' demographic information from the second participatory design workshop.

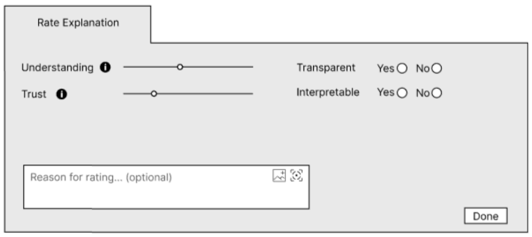

Figure 5: Second alternative to the *Rate Model Prediction* feedback view with a smaller set of parameters.

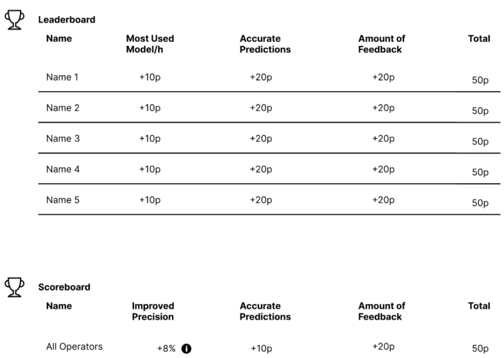

Figure 6: Two versions of *gamification*. The table at the top shows a competitive implementation and the bottom table shows a collaborative gamification implementation.

we presented the XAI components responsible for communicating information to the operators, i.e. how the interface explains its prediction to the users. Second, we asked them an open question: this is how the system communicates with you, how would you like to communicate back? This led to brief reflections on what type of interaction they would prefer. Following this, we provided the operators with printed-out versions of feedback solutions (a selection of these can be seen in Fig. 3, 5, 4, and 6) designed based on the findings from Phase One, asking the operators about their impressions. The operators were encouraged to add or remove features from these design suggestions to better align with their preferences and to design their own suggestions for feedback interactions. Once all feedback solutions had been presented and discussed within the group, the operators were asked to discard any ideas they thought were unnecessary. At the end of the exercise, only the ideas the operators considered useful remained, and most of these had been modified, as seen in Fig. 7.

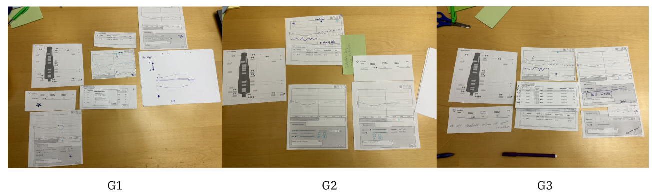

Figure 7: The resulting choices of interface components from the PD workshop. Shown in order of Group 1, Group 2, and Group 3.

6.3 Analysis

The final selection of interface components was cross-checked between all operators and analyzed using affinity diagramming [25, 51]. The data was gathered as Post-it notes and included observations, quotes, and represented their choices in the workshop (their choices can be seen in Fig. 7). The occurrence of each interface component and any additions to the design added by the operators were also noted. This resulted in a large selection of notes, which were grouped based on affinity. These were then combined to create a smaller set of notes representing the sentiment of the grouping. This resulted in three themes.

6.4 Phase Two Findings

The affinity diagram showcases operators' preferences and considerations for the feedback functionalities and gamified scoring systems. Three themes emerged as a result (see Figure 8). The following sections will describe each theme.

Feedback Interaction: Operators highlighted the need for an interactive timeline to facilitate feedback on specific time steps. Interactions such as rating predictions were debated due to their lack of immediate benefit:

Perhaps it could be fun in the beginning, but I think that you would get tired of it after a while because you do not directly benefit from it. (O2)

This type of feedback is only useful for the AI. If it is to be used in the long run it needs to be useful for us running the process as well. (O3)

To address this issue, feedback has to be immediately useful for the operators. Operators preferred the idea of making the prediction graph itself interactive. Doing so enables the operators to place

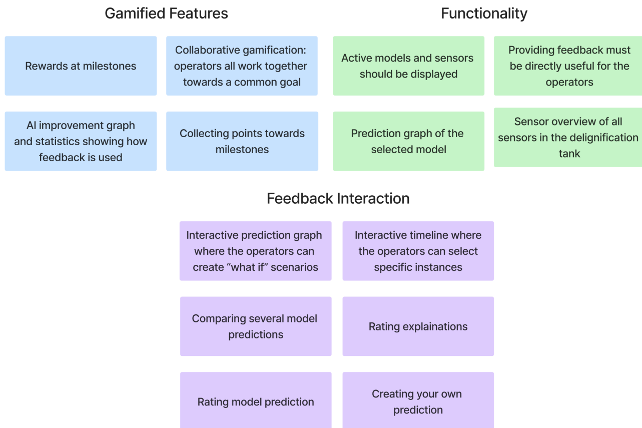

Figure 8: Analysis of the results from the second participatory design workshop.

"what if" sensor data into the prediction, which recalculates the prediction including the updated sensor data. This doubles as feedback since the prediction would be updated with new information and an explanation of what will change and why it will do so. It also becomes a tool for exploring future scenarios and allows the operators to prepare and plan. Outside factors unknown to the model can impact the process, and if the operators could import the relevant sensor data into the prediction to account for this information, the prediction becomes more accurate. For future reference, this will be referred to as the Interactive Prediction Graph (IPG). This idea took shape during the first session, and was well-received throughout all workshops:

You get direct benefit from this quite quickly. And afterward, you can see if you were correct or not, compared to if you send your feedback to somewhere where you do not know where it ends up. (O2)

Gamified Features: The operators agreed that AI improvement statistics were useful inclusions, as they show how the AI improves as a result of feedback. Collaborative gamification, rather than competitive, was favored to maintain unity and motivation, as another operator said:

Sure, I am a competitive person, but I do not think this is suitable here. I really do not think so. We are all working towards the same goal. (O3)

Functionality: Concerning functionality, the operators agree that the sensor overview is essential, allowing them to understand what sensors the AI models account for in their predictions. Naturally, the prediction graph and the ability to plot specific sensor data into that graph should also be present. Another functional insight, mentioned in the first theme, is the importance of making the act of giving feedback directly valuable and useful for the operators. The operators argue that interest in providing feedback will diminish over time if it is only useful for the AI. These insights are essential to ensure that the feedback interactions support long-term usage.

7 Phase Three: Evaluations

Following the Participatory Design, we created high-fidelity prototypes based on the combined insights from the previous phases. To test the design, three evaluations with paper processing plant operators were conducted, consisting of two parts: scenarios using the prototype with the think-aloud method [29] and a brief summative interview targeting the impressions of the feedback interactions. The think-aloud session aimed to gain qualitative insights during usage, while the summative interviews gathered holistic and more in-depth data about the feedback interactions based on metrics commonly used in XAI evaluation methods; focusing on user satisfaction, understanding, curiosity, motivation, and trust [26]. Insights from both methods were analyzed together in a thematic analysis.

7.1 Participants

The evaluations were done with three operators who each tested the interface for an average time of 45 minutes. Following a brief introduction, the operators received a digital consent form. All three operators were male, two were between 40-49 years old and one was between 30-39, two had completed high school, one had completed university, two had eleven or more years of experience, and one had between seven and ten. All the demographic information can be seen in Table 3. It is interesting to note that the expert users in the evaluation on average had more work experience in their current role compared to the expert users of the previous interviews and workshops. Furthermore, none of the operators had been part of the previous interviews or the workshops. Since they were entirely unfamiliar with the design and interface, they offered fresh insights into the functionalities and design of the prototypes.

Participant	Age	Gender	Education	Job	Experience
E1	40-49	Male	High School	Operator	11+ years
E2	40-49	Male	High School	Operator	11+ years
E3	30-39	Male	University	Operator	7-10 years

Table 3: Evaluation participants' demographic information.

7.2 Procedure

The evaluations were conducted remotely, with the operators participating from the control room on-site to more closely mimic real-world conditions. Sessions began with an introduction to the purpose and process of the session. They received a Figma [17] prototype link and read through an interactive interface walk-through. Participants then went through several hypothetical scenarios in the interface using the think-aloud method, vocalizing their actions and reasoning. Each scenario focused on individual feedback solutions, addressing the operator's impressions while interacting with them. The scenarios started with less time-consuming ones, such as: "Now you want to create a comment. In your comment, you want to explain that the prediction relies too much on two sensors. How would you do this?" and progressed to more complex ones, such as "Through the updated prediction, you notice that the predicted kappa value is too low. You see that an H-factor adjustment is needed to keep the kappa value stable. How would you incorporate this adjustment?".

After completing the scenarios, we held a brief summative interview with them to gather more holistic impressions of the interface, its usefulness, and its impact on long-term usage.

7.3 Analysis

Thematic analysis was used to analyze the observations and quotes from the think-aloud session together with the transcribed interview data. Coding was done manually in Figma [17] by two of the researchers of this paper. The codes were mainly deductive, focusing on the topic of the evaluation, however, some inductive codes naturally emerged as well. After the transcribed data was coded, the codes (coupled with the corresponding quotes) were grouped to understand the overall patterns of the data. Themes were reviewed, combined, or renamed as necessary, and relevant quotes were checked for adherence to their corresponding theme. The resulting themes and their connections, along with direct quotes from the operators, are presented in the following section.

7.4 Phase Three Findings

All evaluation results were analyzed and are presented in Fig. 9. The circles represent the overall themes found from the think-aloud sessions and summative interviews, and the squares represent the sub-themes.

The first theme, *IPG Functionality*, refers to the design of the Interactive Prediction Graph (IPG) functionality, shown in Fig. 10. This functionality lets the user place hypothetical *actions* and *effectors* into the prediction graph and see how the prediction changes based on these hypothetical "what-if" scenarios. Participants were generally positive about the IPG, noting its potential to provide insights into both the delignification process and the AI model.

That could be interesting, today we guess a lot, and if you have this then you could test things, and see where the kappa value ends up, it could be interesting. (E2)

Oftentimes we predict things on our own and with this, we can be proactive and see what would happen if we adjust the H-factor or add a few grams of alkali. Would be really nice to see suggestions of what the result of these actions could be. Could be important. (E3)

It is graphically very easy, and you could do fast adjustments and fast comments that save a lot of time. (E3)

The IPG offers *flexibility*, *efficiency*, and *pro-activity*, all of which give the operators insight into the process they work with. This insight, in turn, leads to *increased curiosity*, *increased understanding*, and *increased trust*. This feeds into the second theme, *Long-term usage of feedback features*. Besides the previously mentioned insight, operators' motivation to use the feedback features increased with the help of AI improvement statistics, as they were useful for understanding how the models performed over time and how their feedback contributed to its improvement. The operators were skeptical about the point-collection rewards system, feeling it might detract from the seriousness of the model and is argued to not contribute to increased long-term usage.

8 Recommended Interface Design

This section presents the recommended feedback solutions design baked into the overall XAI interface. The interface builds on a Temporal Fusion Transformer (TFT) model [38], forecasting Kappa in a 90-minute prediction horizon.

Following the evaluations and a last design iteration, the final design integrates feedback solutions into the XAI interface, as shown in Fig. 10. This section explains the core functionalities of the feedback solutions as a result of user involvement in the design process.

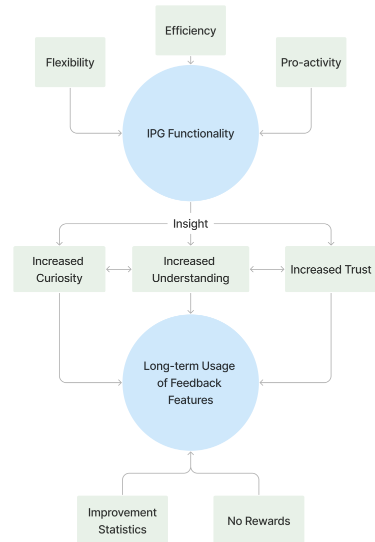

Figure 9: Figure representing the thematic analysis of the evaluations.

8.1 Selection of AI Models

The first feedback solution is baked into the overview of trained models component (Fig. 11). Here, the operators can choose from a selection of AI models with varied parameters and differences in feature importance, allowing the AI models to produce slightly different predictions that are more or less suitable for different contexts. One AI model might be more well-adjusted to producing accurate predictions in an environment where the incoming wood chips in the pulp production process are affected by moisture. Another AI model could be beneficial in the opposite scenario. Depending on the context, the operators can choose the most suitable AI model to produce a prediction. Exploring the technical details of the AI models is outside the scope of this study and we elaborate more on this in Section 10.1. The choice of model is one type of feedback, as the usage of inaccurate models gradually decreases over time and is eventually replaced by other models. This is a kind of natural selection for successful models.

8.2 Interactive Prediction Graph (IPG)

The Kappa forecast component (Fig. 12) has *actions* and *effectors*. *Actions* are tasks operators perform to ensure a stable Kappa, while *effectors* are variables affecting the Kappa. Operators can drag these into the prediction graph, updating and adjusting the prediction with additional information so that it becomes aware of contextual variables such as moisture. This serves three purposes:

- Firstly, it serves as a form of feedback, explaining both what affects the Kappa, and why it affects it. This also effectively

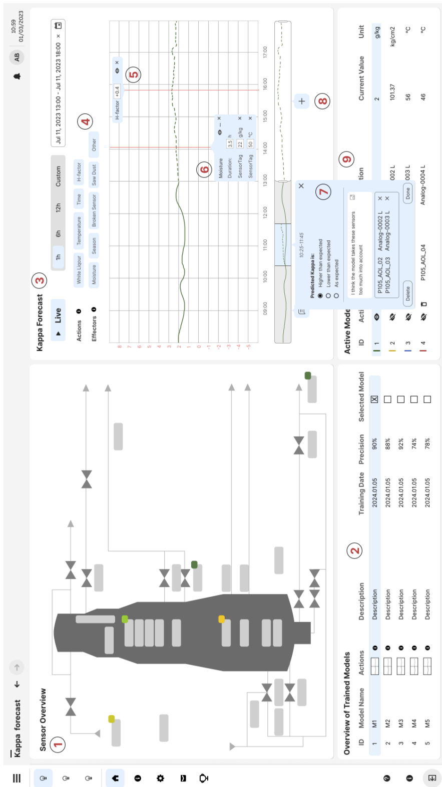

Figure 10: Recommended interface design: (1) sensor overview, (2) overview of trained models, (3) kappa forecast, (4) actions and effectors, (5) an action (H-factor) in the graph, (6) an effector (moisture) with affected sensors, (7) a previous comment, (8) add new comment, (9) active models and sensors in the graph.

Overview of Trained Models

ID	Model Name	Actions	Description	Training Date	Precision	Selected Model
1	M1		Description	2024.01.05	90%	☒
2	M2		Description	2024.01.05	88%	☐
3	M3		Description	2024.01.05	92%	☐
4	M4		Description	2024.01.05	74%	☐
5	M5		Description	2024.01.05	78%	☐

Figure 11: Overview of Trained Models component.

labels the data, which is a current issue since most of the training data is unlabeled.

- Secondly, it provides the operators with a proactive tool where they can freely ask "what if" questions, effectively giving them insight into potential future scenarios and actions. Based on the results from the PD workshop, this functionality should also positively affect the likelihood of providing feedback, as it directly assists them in their work.
- Thirdly, it increases transparency, allowing the operators to understand how much the AI model takes *actions* and *effectors* into account. It allows the operators to "discuss" with the AI model and see how it responds to hypothetical scenarios. Coupled with additional feedback methods (which will be explained below), the operators can specify whether the prediction is adjusted too much, too little, or just the right amount.

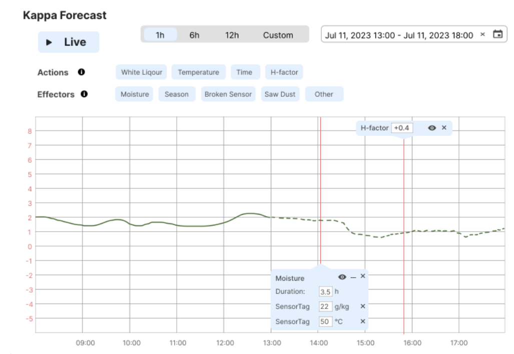

Figure 12: Interactive Prediction Graph (IPG) component with an added action (H-factor) and effector (moisture) to the prediction.

8.3 Dynamic Comments

The dynamic comments (Fig. 13) allow operators to provide quick feedback for specific instances of predictions. Operators can indicate if the predicted kappa is "higher than expected", "lower than expected", or "as expected", and add further context with comments or by dragging sensors into the selection. Coupled with free text, this open-ended feedback addresses the operators' need for detailed, context-specific input. The design also includes interactions for displaying previous comments with details, such as the exact period and the prediction at the time of the comment.

9 Discussion

Both XAI methods for regression tasks using time-series data, and research examining how user-driven feedback solutions for AI should be designed, are underrepresented fields of research [37, 48, 66, 74]. Through this research, we have found that user-centered PD methodologies [16, 59, 64], are important inclusions in designing feedback solutions for highly technical and complex industrial processes with XAI systems working with time-series data.

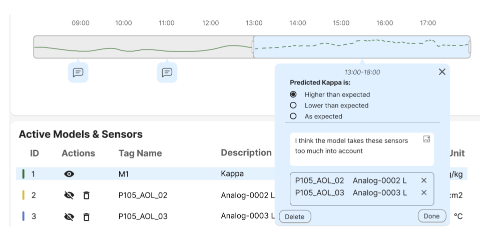

Figure 13: The graph navigation tool showing the time span and prediction the comment is referring to, with the predicted kappa selected to be higher than expected, a free text comment, and affected sensors added into the comment.

Design research contributes to knowledge through inquiry [75]. It lends itself to pragmatic, conceptual, and procedural insights into the approaches chosen by the designers [20]. In this context, we have contributed knowledge through a thorough exploration of the specific industrial context, its expert users, and their continuous involvement in the iterative design process of feedback solutions for XAI systems. Therefore, the resulting XAI interface design and the design recommendations (presented in the following section) are embodiments of the user-centered PD methodologies chosen for this research.

9.1 Design Recommendations

The following design recommendations have been identified regarding how to develop feedback solutions for an XAI system in an industrial context. These recommendations stem from the results of all user-centered PD activities in this research and can be seen as embodiments of the expert operators' contributions to the iterative design process.

(1) **Longevity hinges on immediate usable insights.** To ensure longevity and continued usage of the feedback solutions, the act of giving feedback to the system should be immediately insightful for the user. This means that the act of giving feedback should result in an increased understanding of the AI, the related process, and the operator's current situation. Obtaining such insight requires an immediate response from the system based on the operator's actions. Insight is gained from good XAI methods, and since the ability to give additional accurate feedback to the system is greatly dependent on this [65], we recommend that XAI methods are baked into the feedback solution. Furthermore, utilizing counterfactual examples and hypothetical scenarios that explore the decision-making of the AI as a tool for giving feedback to the system is an effective way to address all these points. As demonstrated by the IPG functionality, feedback, insight, and refined predictions can be combined within a single solution. Previous research has also shown that highlighting the relationship between user interaction and predictions influences the users' preferences for a system [7], supporting the idea that counterfactual examples and hypothetical scenarios are sound approaches to ensure longevity and continued usage of the feedback solution.

(2) **AI model selection enhances trust and feedback.** Having several AI models to choose from with slightly different parameters offers quick feedback, as the most suitable model gets chosen more often based on accuracy and performance. This ensures a natural selection of AI models, providing insight into what type of model configuration works best. An automatic model selector with the same purpose has already been explored [33], and perhaps this could be done automatically in the future. However, there is related research showing that allowing users to explore contrasting features in predictions plays a role in user trust [53]. By generalizing these insights, allowing the user to select between models could have a positive impact on trust, while simultaneously serving as a quick and easy-to-do feedback solution.

(3) **Quick feedback interactions promote usage.** An option for giving feedback should be quick and brief, ideally as simple as selection boxes, as easy-to-do interactions require a lower threshold of motivation to be acted upon [18, 19, 73]. There is a trade-off here, where more brief types of feedback are less informative, but to ensure long-term usage of the feedback solutions, such interactions should be an option.

(4) **Efficient interaction modalities facilitate richer feedback.** The feedback solution should also allow for richer modes of feedback, which should be done through efficient interaction modalities to lower the threshold of motivation required to do so [18, 19, 73]. For example, dragging and dropping larger chunks of information from other parts of the interface into the feedback solution, compared to manually describing that information in text.

(5) **Text feedback should be an option.** Although ideally avoided as it is cumbersome, written text feedback offers flexibility when additional context is required [9], and should therefore be an option within the feedback solution.

(6) **AI improvement statistics motivate users.** The system should show how feedback is used in a meaningful way by, for example, displaying improvement statistics showing how the AI has improved as a result of feedback. This establishes clear goals and purposes for the act of giving feedback [35], which can be argued to increase motivation and long-term usage of feedback solutions.

(7) **Avoid scoring systems and rewards.** Scoring systems and rewards as a means of increasing motivation should be avoided unless it is highly unobtrusive and strictly opt-in [39, 56].

(8) **Display past feedback.** Previous feedback should be visible in the interface so that users can "compare notes" and learn from each other. Previous feedback should also be coupled with the reasoning and decision-making of the AI at that time. This ensures feedback is coherent between users and that they understand how feedback is given in relation to the reasoning and decision-making of the AI.

9.2 User-Centered PD in Process Industry

Designing feedback solutions within XAI systems in industrial contexts through user-centered PD methodologies has, to the best of our knowledge, not been done before. Given the complexity of the Kraft process [2], this approach is necessary to ensure that the feedback solutions adhere to the requirements of the expert operators, which is crucial for the success of AI in industrial contexts [16, 44]. PD is described as a necessary approach to ensure that AI systems are usable [5] as it allows the users to be the experts of their own experience [59, 64] and grounds the resulting design in reality. As is shown in this research, incorporating user-centered PD methodologies for the design of XAI feedback solutions is no exception due to the complexity of the industrial processes and the specific requirements of the corresponding expert operators.

Throughout all phases of this research, nearly all operators stressed the importance of immediate usable insights as a result of providing feedback. This highlights an important consideration in designing feedback solutions within XAI interfaces in industrial

Number	Findings and Recommendations	Description
1	Longevity hinges on immediate usable insights.	To ensure longevity and continued usage of the feedback solution, the act of giving feedback to the system should be immediately insightful for the user. This means that the act of giving feedback should result in an increased understanding of the AI, the related process, and the user's current situation.
2	AI model selection to enhance trust and feedback.	Having several AI models to choose from with slightly different parameters offers quick feedback, as the most suitable model gets chosen more often based on accuracy and performance. This ensures a natural selection of AI models, providing insight into what type of model configuration works best.
3	Quick feedback options promote usage.	An option for giving feedback should be quick and brief, ideally as simple as selection boxes, as easy-to-do interactions require a lower threshold of motivation to be acted upon.
4	Efficient interaction modalities facilitate richer feedback.	The feedback solution should also allow for richer modes of feedback, which should be done through efficient interaction modalities to lower the threshold of motivation required for usage.
5	Text feedback should be an option.	Although ideally avoided as it is cumbersome, written text feedback offers flexibility when additional context is required.
6	AI improvement statistics motivate users.	The system should show how feedback is used in a meaningful way by, for example, displaying improvement statistics showing how the AI has improved as a result of feedback.
7	Avoid scoring systems and rewards.	Scoring systems and rewards as a means of increasing motivation should be avoided unless it is highly unobtrusive and strictly opt-in.
8	Display past feedback.	Previous feedback should be visible in the interface so that users can "compare notes" and learn from each other through previous interactions with the AI.

Table 4: Summary of the design recommendations created in this research.

contexts which could not have been confirmed without employing these methodologies. A user-centered PD approach also hinders the development of unwanted features that could be more acceptable in other contexts, such as scoring systems or other gamified reward systems shown to increase usage and the acceptance of novel technologies in other contexts [12, 14, 72]. Furthermore, the operators' contributions minimized the occurrence of unnecessary feedback interactions which designers unfamiliar with the details of a certain industrial process could deem relevant.

The user-centered PD approach described in this research results in a design tailored for this specific industrial process. Despite this, we believe that the insights from this study could be applicable in other contexts as well. Regarding generalizability, the design itself is specific to this use case, however, the design recommendations could be more universal. For example, the design recommendations that emerged as a result of this research display some overlap with previous research in the area of Human-AI interaction by Amershi et al. [3]. However, it could be the case that specific feedback solutions and strategies for increasing long-term usage vary depending on the context, which underlines the importance of user-centered PD approaches in future studies developing feedback solutions within XAI interfaces in other industrial contexts.

10 Conclusion

In conclusion, our research has demonstrated the inclusion of user-centered Participatory Design (PD) methodologies in the development of feedback solutions within eXplainable AI (XAI) systems in the context of industrial processes involving time-series data. This work addresses the significant gap in research regarding XAI methods for regression tasks using time-series data and the design of user-driven feedback solutions within XAI systems.

By employing user-centered PD methodologies, we have ensured that the feedback solutions developed are tailored to the specific needs and requirements of expert operators in the industrial context of the Kraft process. The iterative design process, which involved continuous input from these operators, has allowed us to create feedback solutions that are both practical and effective. This approach not only validates the design but also ensures its usability and relevance in real-world applications.

Our design recommendations (summarized in Table 4), grounded in the insights gained from the expert operators, emphasize the necessity for immediate, usable insights from feedback, the importance of model selection to enhance trust and feedback quality, and the need for quick, easy-to-use feedback interactions. Additionally, we advocate for richer feedback modalities, the inclusion of text feedback as an option, the display of AI improvement statistics, the visibility of past feedback, and the avoidance of scoring systems and rewards unless highly unobtrusive and strictly opt-in.

The application of user-centered PD methodologies minimizes the risk of developing unwanted features and ensures that the feedback solutions are directly aligned with the operators' needs and the complex nature of the industrial processes they manage. Although the specific design recommendations are tailored to feedback solutions for the Kraft process, they provide a foundation that can be adapted and applied to other industrial contexts, emphasizing the generalizability of our insights.

10.1 Future Work

For future studies, we recommend including more expert operator participants, especially during the evaluation. In this study, a total of 12 unique operators contributed to the design, which is in line with previous research conducted with expert users [40, 52, 62]. However, introducing more expert operator participants in future studies would strengthen the results. Furthermore, it would be beneficial to conduct longitudinal evaluations to fully establish the usefulness of the feedback solutions. In addition, as it is not the main aim of this paper, this research did not touch upon the specific technical differences between the AI models which selection can be used as a feedback mechanism. The technical constellation of these models and how users could intuitively compare them are grounds for future research. We also advocate for additional PD workshops, with a PD session focused on ideation. The following PD sessions would then be conducted in a similar manner to the one conducted in this paper. This would serve to remove any potential bias introduced through the design suggestions used in this PD workshop. Since the practice of incorporating user-centered PD in industrial settings is still fairly unexplored, future work should aim to implement this practice in other industrial settings. A suggestion is to explore if the design recommendations created here are applicable in similar industrial contexts working with time-series data, such as mineral recovery and processing [47].

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