A framework to promote process recommendations through organizational practices

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Abstract. Using artificial intelligence (AI), prescriptive process monitoring techniques suggest interventions to improve the efficiency of business processes and prevent negative case outcomes. These interventions aim to trigger process workers to adapt regular process execution in a specific case. Although this adaptation can aid process performance, process workers often do not react to them. The reasons for this reluctance are still opaque. Technical approaches in human-computer interaction try to increase the user's attentiveness to interventions through prompts or seek to provide explanations for predictions by explainable AI (XAI). So far, these approaches have not sufficiently studied the relevance of the users' organizational context and practices from a socio-technical perspective. This view helps us understand the influences on the willingness to react to system-based interventions. We conducted an analysis of research on prescriptive process monitoring and human-centered AI in organizations and explored an empirical case. By deriving twenty essential requirements, we designed a framework that represents a socio-technical meta-process of how AI-based recommendations could be organizationally embedded. For example, interventions can be amplified by co-workers, managers, and other stakeholders, explanations can be completed by human contribution, and reflection can be promoted by managers to trigger the evolution of AI. This framework can serve as a basis for further research on coordinating the users' interactions with prescriptive process monitoring.

Keywords: prescriptive process monitoring · human-centered AI · organizational practice, socio-technical design

1 Introduction

Organizations continuously seek to improve their efficiency through business process management (BPM) [14]. To aid these efforts, they have started to utilize data-driven techniques from the field of process mining, which allow them to discover, analyze, check, and monitor business processes. Since their inception in the early 2000s, process mining techniques have expanded from discovering processes based on event traces in information systems to include techniques that predict the outcome of single process instances employing AI-driven methods [36]. More recently, prescriptive process monitoring techniques have emerged that intervene with recommendations based on such predictions to reduce the probability of negative case outcomes [31].

Despite prescriptive process monitoring techniques providing relatively accurate predictions, e.g., recommending the next activity to be executed [11], adoption has been scarce. Existing empirical studies indicate that process workers oftentimes do not follow recommendations even if they understand them [12]. Recent studies address user interfaces that support process workers and analysts in using prescriptive process monitoring [32] by, for example, explaining recommendations [31] or nudging them towards abiding by recommendations [33].

These studies, however, focus on individual process workers and analysts which does not seem sufficient to increase abidance by recommendations. Process workers in particular operate in a larger organizational context that has a set of policies and social norms [10]. They have to interact with different roles, like supervisors and managers [40]. Organizations also might operate multiple information systems that can provide contradicting information. These aspects, among others, can prevent process workers from abiding by recommendations. Moreover, focusing on single process instances might limit the potential to utilize recommendations created by prescriptive process monitoring as a basis for sustained change of organizational practice.

To address these issues, we thus ask the following two main research questions:

RQ$_1$. *Which aspects of organizational practices could influence the adoption of AI-based recommendations for process handling, and how can these aspects be integrated into a comprehensible socio-technical framework?*

RQ$_2$. *How can recommendations be utilized as a basis for the continuous improvement of organizational practices and technical infrastructure?*

To answer these questions, we first discuss existing work in the context of prescriptive process monitoring and of human-centered AI (section 2) which we will use to extract initial requirements for our framework (section 3). Adding requirements from an approach that emphasizes the relevance of keeping the organization in the loop proposed by Herrmann and Pfeiffer [23] and an empirical case study, we proceed to describe the design of our proposed organizational recommendation handling framework (ORecH) framework (section 4). The framework includes possible varieties of how interventions provided by process monitoring can be organizationally embedded to foster process workers' willingness to abide by recommendations. A concluding discussion (section 5) provides answers to our research questions, sheds light on limitations, and outlines possibilities for further research.

2 Background

In this section, we will discuss existing recommendation approaches (section 2.1) as well as current works on human-centered AI in organizations (section 2.2). These will serve as a basis for the development of our framework.

2.1 Prompts and process recommendations

The term prescriptive process monitoring refers to methodologies that propose interventions during the execution of a case with the aim of optimizing its outcome in relation to predefined key performance indicators (KPIs) [47]. These methodologies have successfully been developed for different domains, such as manufacturing [18] and healthcare [49]. Researchers have proposed a number of different approaches that can provide interventions, e.g., related to resource allocation [3], control flow [11], or both [47]. In the context of this paper, we will focus on control flow interventions. This means that the interventions we discuss require a process adaptation or a deviation from the typical process sequence.

Current prescriptive process monitoring approaches related to control flow propose interventions that can roughly be divided into two categories:

1. **Alarm-based**: Approaches such as the one proposed by Teinemaa et al. [48] raise an alarm when a KPI, such as the cycle time, passes a specified threshold. These approaches do not propose a specific intervention. Instead, they leave the decision about how to intervene to the process workers.
2. **Proposing a specific action**: Approaches such as the one proposed by Khan et al. [28] compare a running case with past cases and assess the benefits of conducting a specific activity to optimize performance. Similarly, approaches such as the one proposed by de Leoni et al. [11] suggests the next activity during process execution.

Thus, the focus of these approaches mainly lies in proposing single interventions to individual process workers working on a specific case. We will extend this perspective by considering the organizational context in which a case is processed. It should be noted that existing approaches consider policies for prescribing interventions. These policies, however, are not organizational-level policies. They are rather thresholds or KPIs that govern when an intervention is triggered. The aforementioned approach proposed by Teinemaa et al. [48], for example, provides an alarm to the process worker without discussing the broader organizational context. Organizational policies or social norms have not been extensively studied in the context of prescriptive process monitoring so far.

2.2 Human-centered AI and organizational background

AI-based process monitoring and intervening during process execution aim to increase flexibility as already discussed in the context of workflow management by the discussion on exception handling and flexible solutions [20, 27]. To react flexibly during routine process execution supports process workers to feel in control and to employ their competencies. These aspects of control and flexibility are subject of the communication within groups of process workers in a socio-technical context. Our theoretical approach is to frame socio-technical systems and processes as an intertwinement of social and organizational practices on the one hand with an infrastructure of technical artifacts on the other hand for the purpose of task handling. This intertwinement is instantiated by human-computer interaction that is shaped not only by technical possibilities but also by organizational practices that include an ecology of tasks and roles [6, 29]. Such organizational practices are part of social practices that inevitably require interaction and communication between humans [35]. Communication within socio-technical systems basically goes beyond the mere information exchange of information and includes opportunities for informal roles and encounters [1]. We suggest that socio-technical design is focused on processes [24] that are continuously appropriated [19] by the roles involved that contribute to the dynamic evolution of the socio-technical processes [21]. Thus, socio-technical systems inherently employ and advance the competencies of involved people and support them to influence their workload.

Approaches that value socio-technical perspective when using AI are summarized by the concept of "human-centered AI" (HCAI) [44, 46].HCAI supposes a long-term role for humans in the application of AI systems [13, 30, 43] from a socio-technical perspective. It aims to foster and develop human competencies and capabilities as well as improve AI solutions and assumes that humans and AI together deliver better results than each of them alone [13]. For instance, Jarrahi describes different strengths of humans and AI in decision-making, arguing that humans are better at dealing with uncertainty and equivocality [26]. Both might be important when dealing with human stakeholders. Thus, humans can take on a variety of roles and jobs in the course of task sharing with AI [38], and they should have the opportunity to reject AI results [41].

HCAI addresses sequence flexibility where AI results are presented, for instance, in regard to the question of what will take place first: The drafting of a decision by the human or presenting the outcome of AI [17]. According to this approach, instead of immediately proposing how to proceed, the system could provide an alarm to trigger the process worker's ideas about altering the standard execution of a process. Then, the idea of the process worker is compared with what the system recommends.

Flexibility in HCAI includes the possibility of intervention, on the one hand, by the system [16], which is comparable to the approaches presented in section 2.1. Thus, AI becomes a possibility to critically accompany human experts and aid them in avoiding mistakes and identifying opportunities for improvement. On the other hand, a human actor, e.g., the customers who benefit from a process, can intervene if their needs or priorities might change [25, 45].

HCAI requires that users, in our case process workers, understand why and how certain results of AI are proposed. Therefore, explainable AI (XAI) aims to reduce the complexity of machine learning systems and to explore the properties of processed data so that the influence of certain features can be understood [37]. Examples for XAI are interactive ranking mechanisms for features that influence an AI-outcome [8] or explanation plots [42]. Identifying and comparing past cases that are similar to a current case can also aid explainability, especially if cases are identified that are slightly dissimilar, and illustrate how subtle variations of the underlying situation can influence AI outcomes [4].

A reasonable task sharing between humans and AI requires critical reflection and, thus, new ways of understanding and dealing with AI results. This reflection needs deliberative, analytical thinking [15] that has to be stimulated, for example, by Cognitive Forcing Functions [9], such as prompts, delays, etc. This triggering can help counter the human tendency to place too much trust in automated systems and thus supports trust calibration [39].

As outlined by Herrmann and Pfeiffer [23], all these possibilities covered in HCAI need organizational practices that accompany them and to lay a basis for their success. *"A key challenge to the implementation and adoption of intelligent machines in the workplace is their integration with situated work practices and organizational processes"* [50]. For example, integrating AI systems and employees can be seen as an organizational task within an onboarding process that has to be planned [5]. XAI and trust calibration are highly related to social transparency and the ability of other humans to give explanations [15] or to judge an AI outcome and whether one should trust it or not [2].

Herrmann and Pfeiffer [23] propose a systematic scheme for considering organizational practices that support human-centered AI. They address a set of managerial activities that influence the success of applying AI and implementing HCAI: managerial coordination has to determine how AI-based results are handled. It is closely related to human resource management (HRM) with respect to teaching people about how to use AI and determining roles that deal with AI. The quality of the involved managerial decisions also depends on coordination with the external world, which includes all stakeholders and organizational units that are not subject to the process management application. Similarly, ongoing changes have to be considered with respect to the contextual factors that accompany the application and the performance of a process management system. These managerial activities are closely interwoven with end-users employing AI-results to perform their tasks and with the continuous evolution and improvement of AI. Fig. 1 in section 3.2 depicts this interplay. We have adapted this scheme to focus on process workers.

3 Method: Deriving requirements for designing the organizational recommendation handling framework

To answer $\mathbf{RQ}_1$ and $\mathbf{RQ}_2$), we derive requirements from existing work (section 3.2) and an empirical case study (section 3.3).

3.1 Requirements from the literature background

Based on literature we identified the following 8 basic requirements. The framework should mirror the participants' (managers, workers, and their teammates) possibilities to...

R1 . . . choose between interventions that provide an alarm vs. offering recommendations for the next action to be carried out.
R2 . . . find a coordinated response on an alarm
R3 . . . make coordinated decisions about how to handle a recommendation
R4 . . . explain the reasons behind an alarm or a proposal for adaptation
R5 . . . handle a recommendation flexibly, including its rejection or its modification, or having the opportunity to first reflect on an appropriate next action before AI specifies a recommendation
R6 . . . not only be the addressees of interventions but also be able to intervene in the AI's behavior of providing recommendations
R7 . . . make comparisons with similar cases of reacting to interventions
R8 . . . allow for coordinated trust calibration.

3.2 Requirements from "Keeping the organization in the loop"

We derive further requirements from the scheme proposed by Herrmann and Pfeiffer [23] (Fig. 1) that conceptualizes the approach of keeping organizational practices and management in the loop when introducing AI. The scheme covers four areas of management activities (a,b,c,d) that accompany and promote using AI and support its evolution by the process worker who handles cases. Here, the original task is the execution of cases, and AI contributes more or less appropriate proposals that help to mitigate the violation of KPIs. The scheme expresses that the interplay between dealing with completing the original tasks, including AI outcome, and continuous improvement of AI has to be coordinated. This coordination covers the corresponding activities of human resources management (HRM). Furthermore, the inclusion of AI has also to be aligned with changes, e.g., new legal requirements, and with external stakeholders, such as other companies and institutions that might contribute to or benefit from the original task. Thus, the scheme leads to further requirements by which the organizational handling of recommendations should make it possible to

R9 . . . take the interplay between several roles into account
R10 . . . promote collaborative flexible handling of AI-outcomes and AI-initiated tasks
R11 . . . relate explanations and reflection to the need for the continuous evolution of AI
R12 . . . coordinate AI-evolution in accordance with quality assurance and ongoing changes
R13 . . . take external views into account, in particular, those of clients being affected by process handling
R14 . . . maintain continuous awareness of interventions and their handling

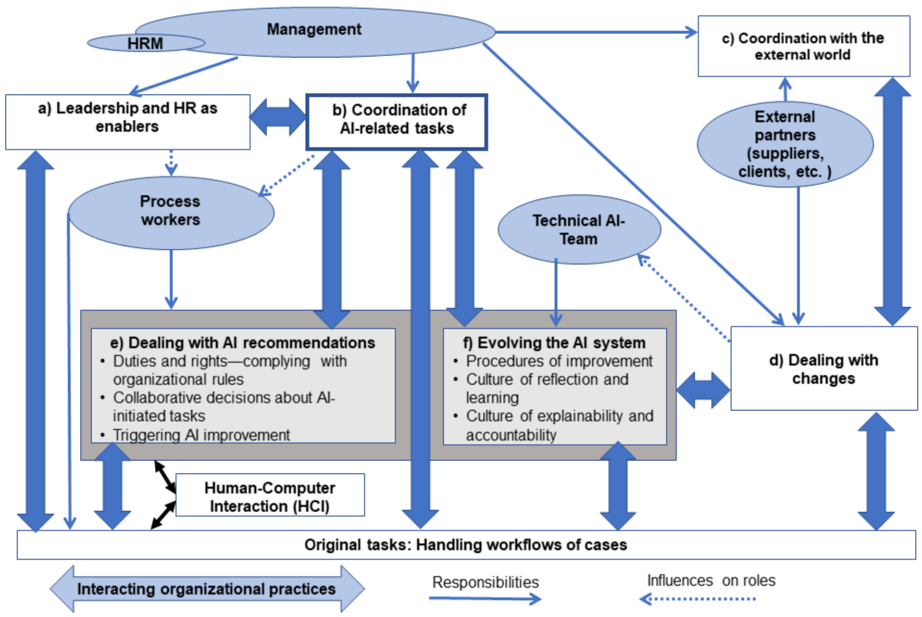

Fig. 1. Scheme of AI-related organizational practices according to [23]

3.3 Case-based requirements

To further advance our requirements, we refer to a concrete practical case where a continuous change of processes and dynamic process execution were pursued. During the last eight years, we have collected data while consulting a health insurance company about improving its customer service processes with the goal of maintaining the customers' loyalty. Together with the company, we analyzed the process execution of service employees who handled cases such as dealing with refund requests or with applications where customers ask whether a certain health treatment or preventive activity can be totally or at least partially refunded. The project was not technically but organizationally driven and helped to derive requirements if regular process handling needs situational adaptation.

Since more than 20 processes had to be redesigned and deployed over more than 40 branches, the original question was whether and how such an endeavor could be supported by a participatory design approach based on workshops and a step-by-step inspection of the workflows of process execution [22]. The goal was to enable the change management team to employ participatory methods for the process redesign. The project covered the following phases: guidelines and instruction for the change management team; running demonstrative workshops to orient the change management team; reviewing of re-designed process models; accompanying the roll-out of the newly designed processes. During the project, the following documents were produced that form our data basis: Process diagrams, hints to be added to work instructions, excel sheets that document needs for technical improvement, and minutes of the meetings and workshops.

Besides supporting the original focus of the project, the empirical material provided several hints on situations where flexible process handling was necessary and the members of the customer service teams had to be directed to react appropriately. We identified six examples (Table 1) for the need for flexible reactions that inform the development of our framework (section 4). These examples are derived from our data basis. For the understanding of the examples and their implications, the workshops were the most decisive. We took part in 7 workshops with 10 participants on average where various stakeholder groups were present (managers, service team leaders, operative forces). The six examples were selected from the extensive set of proposals for changing customer service processes with respect to the following criteria:

- They refer to flexible measures that are not constantly initiated but only from time to time, depending on the properties of a certain case.
- They were considered reasonable by all stakeholder groups that participated in the workshops.
- The workshop participants were concerned about how proposing such a new measure might be communicated in selected situations.
- The workshop participants were concerned that the process workers have to be convinced to realize the new measures in situations where they were recommended.

Table 1. Empirical examples for flexible interventions

ID	Example
1	Seek direct contact with the customer if her / his application has to be rejected.
2	If the reimbursement for preventive workout sessions cannot be paid because the recognition of the fitness center is still in process - then the decision on the reimbursement is put on hold instead of sending a rejection.
3	No rejection if a possible appeal against the decision can be expected, and the handling of the appeal will be more costly than the reimbursement the customer has applied for.
4	Regularly, the process worker checks first whether the customer has submitted all data needed. In certain cases, before asking the customer to complete the data, the process worker should check whether the customer has a real chance of getting refunded.
5	If anything is known about a conversion of the customer's contract terms, these have to be checked first before processing the application for reimbursement.
6	Under certain conditions, it no longer makes sense to put a transaction on resubmission, for example, if the customer has already been reminded three times to provide missing data.

The advantage of these exemplary measures was that there were no doubts about their appropriateness, and the remaining challenge was to instruct and motivate process workers to abide by them. By analyzing the discussions of these examples during the workshops we identified further requirements such as offering possibilities to

R15 . . . understand whether a recommendation for the next activity means inserting a new activity, replacing another activity, or changing the sequence of activities.
R16 . . . clarify why a case that is affected by a recommendation is different compared to others where the regular procedure applies
R17 . . . understand the recommendation's effect on relevant KPIs also including the workers' workload and customers' satisfaction or loyalty
R18 . . . get explanations of how the intervention refers to legal aspects or to the organization's culture
R19 . . . provide help if following a recommendation proves unsuccessful or is not executable (e.g. if a customer cannot be reached via phone)
R20 . . . also include proposals for adaptations of the regular process that are detected by human actors

In what follows we refer to the requirements of this section as a rationale for the design of a framework for organizational recommendation handling.

4 Proposed socio-technical framework

At the very moment when an AI-based recommendation is displayed during process execution, this can be considered as a starting point for a sequence of meta-activities (Fig. 2) that represent measures of handling AI-based interventions and the subsequent possible adaptations during process execution. The most important consequence of the scheme in Fig. 1 is to widen the perspective: Thus, Fig. 2 does not only include activities of the process worker when interacting with AI (blue outlined, rounded rectangle) but also activities in the organizational context that can be run by managers (process owner or team-leader) or team-members (R9). The green highlighted path in the diagram (Fig. 2) represents the most direct way of dealing with a recommendation, where the process worker accepts the intervention, and no further explanations or modifications of the recommendation are necessary. Generally, for each intervention recommended by AI-based prescriptive process monitoring, the process workers should have a routine that allows them to assess whether a recommendation is appropriate or not (R3, R10). This is a basic pattern of the HCAI discourse and a fundamental step of keeping the human in the loop [38]: The user should be prepared to veto a recommendation [41] (R5), and overtrust in AI should be avoided [39] (R8). During the workshops of the empirical case (section 3.3), it became clear that the process workers should critically reflect on each adaptation and its effect (R17, R18) to determine whether it is reasonable to abide by the recommendation or to modify them. If the AI-based process prescription only provides an alarm [48] (R1), the process worker (or her/his colleagues) are involved anyway since they have to detect a useful adaptation to react to the alarm

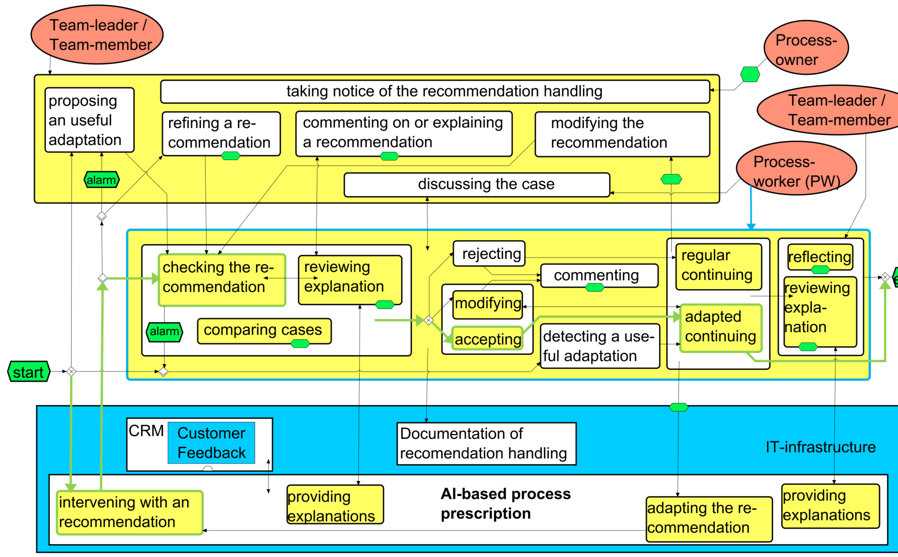

Fig. 2. Socio-technical meta-activities of the organizational recommendation handling framework (ORecH-Framework)

(R2). The next step for the process worker in Fig. 2 is optional, as indicated by the green hexagon. It refers to asking for an explanation, as suggested as an option by the XAI discourse within HCAI [7, 34] (R4). We propose explanations to be asked before applying a recommendation or afterward, or both. Explanations can be complemented or substituted by applying case comparison to see how the recommendation worked in other cases. This case comparison is also proposed by HCAI [4] (R7). It can help to find useful adaptations if an AI-based process prescription only provides an alarm [48], and it helps to understand the particularity of the case in the process (R16).

Explanations support the culture of reflecting on AI (R11) as proposed by Herrmann and Pfeiffer [23] (see Fig. 1, f). After assessing the appropriateness of a recommendation and possibly asking for explanations, the process worker has three options: just accepting the recommended adaptation, rejecting it, or modifying it. These options are related to "dealing with AI-recommendations" (Fig. 1, e) in the scheme of Herrmann and Pfeiffer [23] (R10). Subsequently, the process worker continues working on the case. Before doing so, s/he can optionally leave a comment in the system about the reason for how the recommendation is dealt with. Commenting is also an element of the culture of reflection (Fig. 1, f). It has to be noticed that the modification of a recommended adaptation can also take place after the worker has already started to follow this recommendation (R19). Reflection can also take place after the work on the case is completed and might possibly include seeking further explanations. The activities of the process workers, as depicted in the blue outlined rectangle (Fig. 2), can also include that they, by themselves – without an intervention – might have ideas about how a process execution can be adapted under the conditions of a certain case (R20). This possibility corresponds with the variations of possible roles people can take when interacting with AI, as discussed, for example, by Muller and Weisz [38].

The concept of taking the organizational context into consideration is represented by the two upper rectangles in Fig. 2. First of all, with respect to the management's responsibility for coordination (Fig. 1, b), one has to be aware that recommendations are proposed and understand how they are handled (R14). Furthermore, also the team leader or a team member can intervene, e.g., with their own recommendation for adapting a concrete process execution for a particular case (R20). While AI can do this based on process monitoring, humans can intervene based on their practical experience. In the empirical case, we examined, this type of reciprocal support in a team was highly valued. Based on their practical experience, the team of process workers can also try to refine recommendations that are suggested by AI, it can help to explain their appropriateness or comment on it (R17, R18), or it can help to modify a recommendation if the need for modification becomes apparent (R19). The green hexagons depict that many of these options are not mandatory. They will not take place for every possible recommendation but are a basis for the continuous evolution of AI (R12) (see Fig. 2, f). All in all, the organizational context mirrors similar activities as those that are provided by AI and vice versa, and – on a meta-level – the colleagues of a process worker can trigger him or her to adopt the system-based recommendations.

In what follows, we explain how the framework helps to support the examples presented in Table 1.

Example 1 in Table 1 includes a situation where it might become obvious during handling a case that the system's recommendation to call the customer has to be modified if a customer cannot be reached via phone (R19). Subsequently, the AI recommendation might need to be more detailed: not just telling the process worker to make a phone call but also when to call and how many times. This refinement can alternatively be provided by the process workers themselves or by the team leader, or even by a team member. If the customer cannot be reached or is angry about having been called, a more advanced AI would be able to monitor the consequences of its recommendation and modify its interventions for further cases.

Obviously, the recommendation in example 1 (Table 1) includes additional work, i.e., conducting phone calls. Similarly, example 2 also requires additional work. In these instances, an ex-ante explanation can be helpful for the process worker's acceptance so that s/he understands why additional work is reasonable. We suggest that the explanation is more strategical, management-oriented, and less related to the rationality of the AI system's inferences (R18). Consequently, it is reasonable to complement AI-based explanations by the team leader or another team member. Other examples, such as 4-6 in Table 1, cause less work, and therefore process workers might just follow the recommendation without seeking further explanation. Apparently, interventions should include a hint of whether they help save work for the process worker or whether they include more steps than are regularly needed (R15, R17).

In the second example (Table 1), the process workers' willingness depends on how far s/he is supported to put a case on hold to get it resubmitted after some time. If the information system supports a resubmission, the adaptation of the regular process execution is more likely accepted than in situations where process workers have to organize the resubmission by themselves. It might be appropriate to compare this to other cases to assess how long it takes until a fitness center is recognized (R7). With such a comparison, the process worker might specify the deadline for the resubmission. The whole issue of delayed recognition of a fitness center might also become the subject of a team meeting. Also, the decision to be made in example 3 (Table 1), whether rejecting an application is appropriate or might lead to losing a client or to causing extra costs, is not only a question of AI intervention but also a point of discussion between those team members who know the customer or the situation, or have experience with this kind of cases (R18). In this context, it might also be relevant to compare other insurance companies handling such situations and whether changes in handling certain legal regulations are on their way (see Fig. 1, c and d) (R13). To understand the customers' possible reactions, taking additional information into account – as provided e.g. by a customer management system (CRM) – could be considered as well (R13). Thus, the whole context – including the available technical infrastructure (see Fig. 2) – has to be considered.

Examples 4 and 5 in Table 1 are recommendations that can help process workers save work. Thus, it is not reasonable to start investigating or discussing with others whether a recommendation makes sense because this would imply more work than just following the recommendations. However, if the recommendations in these examples prove irrelevant several times, process workers might want to see an ex-post explanation by the system or by others to understand what might have led to inappropriate recommendations and finally to a reflection and to comments on the system. Later on, the collection of comments can be evaluated to improve system-based recommendations (R12).

Also, example 6 can help to save work for the process worker since s/he can close a case instead of waiting and going on later. In this situation, it might be hard to find out whether an intervention was really appropriate or not. Here a critical attitude of the employee is even more relevant to prevent her or him from closing a case prematurely. In these cases, it might be reasonable that the process worker documents a short comment on why s/he thinks that a recommendation was considered reasonable or not. This example clearly illustrates the need to apply prompts that stimulates critical thinking and reflection [9] (R8).

5 Discussion and conclusion

5.1 Research questions

Based on our analysis in section 4 and on the proposed framework (Fig. 2), we can answer the research questions as follows: We suggest that the process workers can flexibly react to an alarm or recommendation, allowing them to feel as staying in control, which is an important aspect of motivation to be considered in socio-technical systems [21]. The influential aspects ($\mathbf{RQ}_1$) for the process workers are the following additional reactions and activities besides the regular process execution:

- checking the appropriateness of a recommendation
- asking for and reviewing explanations that either stem from the team or from the AI-system
- applying case comparison
- rejecting, modifying, or accepting the recommendation
- detecting a useful adaptation in the case of an alarm
- commenting and/ or discussing the case with others
- reflecting the recommendations with the team in the light of the completion of a concrete process execution

Most important is that the process workers' activities are embedded in an organizational context: they know that their coworkers are aware of their way of handling recommendations, that others are willing to help deal with recommendations by explaining them, correcting and refining them, and reflecting on them. The team itself can also provide recommendations so that AI-based interventions appear just as a completion of what, anyway, is the norm within an organization. Process workers know that they are allowed to reject a recommendation and that the team can be the addressee of complaints if the process workers think the AI system overburdens them with an overload of inappropriate recommendations. The variety of possible reactions of process workers still requires their own judgments, the application of their knowledge, and practical experiences and aids to promote the development of their competencies. In particular, the approach of addressing an alarm using their own ideas of how the regular process execution might have to be adapted requires process workers to activate and develop their skills.

This ongoing enhancement of capabilities and competencies is a source of continuous improvement (see $\mathbf{RQ}_2$) and socio-technical evolution [21] that helps to increase the quality of flexibly adapting the regular process execution in concrete cases. Furthermore, reflecting the handling of a concrete case and the appropriateness of a recommendation that was related to this case can result in an improvement. By considering the comments and reflections on several cases, the team or managers can come up with proposals for how organizational practices or the technical infrastructure – including AI-based process monitoring – could be improved. These improvements could include instructions or routines of how specific types of alarms or recommendations could be dealt with. Additionally, cases can be discussed with the process workers where they have rejected certain recommendations, and management can try to convince them to take these recommendations more seriously. As the proposed framework (Fig. 2) makes clear, such a discussion can only be initiated if the organizational practices provide enough opportunities to be aware of the handling of recommendations. On the technical side, it would be advantageous if the handling of recommendations is thoroughly documented and if the AI system interacts with a customer management system (CRM). Consequently, process monitoring should not only cover the regular process execution but also the effects that are caused if the process worker follows a recommendation. This can lead to a step-by-step improvement or refinement of the recommendations over time. Observing the effects of modifying the regular process execution should not only happen if the modification is caused by an intervention of the AI system. It should also take place if the modification is caused by the process workers themselves or is initiated by their teammates.

If a series of system-based recommendations appear inappropriate for the process worker or cause distraction and stress, there should be a possibility to suppress them, but not by just switching them off. Here, it is more appropriate to provide an intervention mechanism as proposed by Schmidt and Herrmann [44], who suggest that such an intervention only selectively stops an automated process - either for a certain period of time or for a certain kind of situation (R6). That means that the process worker can specify a certain time period or certain type of cases for which the submission of recommendations is interrupted.

5.2 Limitations and further impact

In this paper, we presented a theoretically developed framework that was conceptually related to the service processes of one company in a specific domain. The framework now needs to be evaluated with further cases in different domains. Moreover, we created the framework based on published works. Since the field of prescriptive process monitoring is just emerging, we expect that there are technical approaches that are used in practice that have not been published yet and that we subsequently missed. In addition, we utilized the lens of keeping the organization in the loop [23] to arrive at an initial set of managerial activities and organizational routines that should be considered. We expect an evaluation to reveal additional organizational aspects. Similarly, it is possible to identify additional aspects to improve the socio-technical interplay between technical infrastructure and organizational measures. Further empirical evaluation might include researchers with different perspectives to interpret the data and collaboratively avoid biases when projecting relevant organizational measures.

What we have achieved so far is a framework that can guide managerial decisions when introducing AI-based process monitoring and interventions. Managers might use the proposed framework as a checklist to select measures that are relevant for their context and check whether they can help to promote process workers' readiness to adopt system-based recommendations. The framework can also serve as a conceptual model for further empirical research by providing factors that can be varied and tested with respect to their effects.

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