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Human-in-the-loop machine learning: Reconceptualizing the role of the user in interactive approaches

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ABSTRACT

The rise of intelligent systems and smart spaces has opened up new opportunities for human–machine collaborations. Interactive Machine Learning (IML) contribute to fostering such collaborations. Nonetheless, IML solutions tend to overlook critical factors such as the timing, frequency and workload that drive this interaction and are vital to adapting these systems to users' goals and engagement. To address this gap, this work explores users' expectations towards IML solutions in the context of an interactive hydration monitoring system for the workplace, which represents a challenging environment to implement intelligent solutions that can collaborate with individuals. The proposed system involves users in the learning process by providing feedback on the success of detecting their drinking gestures and enabling them to contribute with additional examples of their data. A qualitative study was conducted to evaluate this use case, where participants completed specific tasks with varying levels of involvement. This study provides promising insights into the potential of placing the Human-in-the-Loop (HitL) to adapt and reconceptualize the users' role in interactive solutions, highlighting the importance of considering human factors in designing more effective and flexible collaborative systems between humans and machines.

1. Introduction

Technological advancements, cutting-edge systems and intelligent solutions are starting to accelerate the evolution of future environments (e.g., homes [1], cities [2], workplaces [3]), creating novel data-driven applications in varied domains as mobility [4,5], healthcare [6–8] or agriculture [9,10]. Now, those advancements go much further than implementing technology to achieve a digital transformation goal. The new wave of emerging technological systems may also create interactive spaces where people and technology jointly collaborate towards a shared endeavour (e.g., saving energy [11], adopting healthier habits [12]). However, promoting such collaboration entails lowering the barriers that hinder the effective involvement of individuals and their interactions with the technology [13]. Thus, the user's role needs to be carefully revisited to reduce their reluctance to be part of this new scenario, engaging users to collaborate with emerging smart solutions actively and not see them as a threat [14].

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This conceptualization falls within the scope of the so-called Hybrid Intelligence, whereby humans are included in the loop of Artificial Intelligence (AI) systems [15], creating Interactive Machine Learning (IML) solutions [16]. Furthermore, the collaboration proposal can be framed in the Human-in-the-Loop (HiTL) concept, a new paradigm in which users are engaged to improve and personalize automatic AI-based solutions [17]. In such a scenario, the role of the user is to interact with the learning system and provide feedback, guidance, or input when needed. Besides, the user can monitor the system performance and intervene if necessary while benefiting from the system by receiving outputs, suggestions, or recommendations. The personalization of Human Activity Recognition (HAR) models through IML is an example of the interaction between users and technology to improve a learning system for the classification of human movements and actions using sensory data. In such a case, using a base model trained with generic data may not perform well in real environments or with new users [18]. As a result, personalized models that consider the particularities of the end-user are necessary to enhance the user experience. To this aim, IML applied for HAR solutions proposes a more active role of end-users, in which they are involved in helping the learning system to improve its detection capabilities throughout time. This collaboration is driven by providing new data, in the form of correct labels, for some of the system's predictions [19]. In essence, through HiTL, users can teach the system. This results in a more user-centric system, which has been shown to increase acceptance and adoption in previous research studies [20,21].

Nevertheless, there are several challenges in interacting with users, including engaging them to actively collaborate with emerging smart solutions, particularly those based on AI [22]. Therefore, creating intelligent systems that can be adapted to users' unique preferences has become increasingly essential for more effective and efficient collaborations [23]. This is specifically relevant in environments such as the workplace, where inadequate interactions with intelligent solutions and technologies can hinder performance and be perceived as a distraction at work [24], lowering its potential to enhance productivity and improve the overall work experience [25]. At the same time, despite the user's significant role, IML approaches often overlook the importance of human perception, engagement and willingness to participate in this collaboration [26,27]. Thus, these solutions tend to pre-define the degree of involvement, mode of interaction, and cognitive load rather than empowering users by giving them greater control over their interaction preferences [28,29]. In the light of the relevance of human factors, IML solutions should be developed to cater to diverse user types, contexts, and tasks and facilitate user learning and empowerment, mainly when the required actions involve an effort from their side [30–33]. This means that these solutions should be adaptable enough to modify their functionality based on the user's preferences and context to enhance the usability and value of the system for each individual [34]. All this, while also considering that user interaction can vary depending on context or the perceived outcomes of their effort [35].

In order to cope with these needs, in this work, we present and evaluate a novel interactive system called the 'Smart Drink Monitoring System', which focuses on enhancing employees' hydration habits in the workplace while also assessing the effectiveness of IML approaches in this context. For that, our solution provides a practical and user-centric approach to HitL that lets users choose their preferred collaboration preferences. This system is conceived as an Internet of Things (IoT) solution designed to detect the drinking gesture automatically. The system comprises a device that monitors users' actions and provides quick feedback, as well as two Graphical User Interface (GUI) applications through which the user can customize the system. Through these tools, users can generate new annotated data proactively or reactively and modulate their degree of involvement in the learning process. A qualitative evaluation of the system was conducted in a supervised lab environment to obtain insights into user opinions towards the relevance of personalization and adaptation in IML solutions. Guided by the researchers through two overarching research questions (1. Which is the willingness of the user to be involved in the process of obtaining more accurate predictions? 2. Which is considered a good trade-off effort between the improvements and the time commitment to help the system learn?), this experiment involved 12 participants who tested the system's accuracy in detecting water consumption and performed specific data annotation tasks with different levels of user involvement.

In essence, this study focuses on promoting a human-centric perspective to IML, with a particular emphasis on personalizing the interaction and modulating involvement to engage and motivate users in HITL approaches. This underscores the importance of understanding the human factors that drive interaction between users and technology and how they can be applied to specific collaborative scenarios, such as data labeling in hybrid approaches and other use cases of intelligent systems. Furthermore, the results of this intervention provide insights into designing interactive work environments and developing more adaptable and collaborative learning systems. Overall, this work offers two valuable contributions towards effective human–machine interactions:

- We introduce and evaluate a new intelligent system from a HITL perspective that prioritizes users in the workplace context. The system allows users to personalize their interaction and control their involvement level, leading to a more user-centric and flexible approach to IML.
- We provide insights into how to engage users to support intelligent systems and highlight the importance of prioritizing user involvement and personalization in designing such systems. The findings emphasize the need for more adaptable and flexible learning systems.

The rest of the research manuscript comprises various sections, starting from Section 2, which analyzes existing efforts in defining IML strategies. Section 3 describes the Smart Drink Monitoring System, designed as a use-case prototype for the qualitative evaluation. Then, Section 4 describes the procedure of the conducted evaluation. In Section 5, we summarize the main finding obtained through the conducted evaluation. Finally, we conclude this work in Section 6 and Section 7, which include the final remarks and insights gathered throughout this part of the work and conclude based on the obtained results and its analysis.

2. Related work

Traditional Machine Learning (ML) approaches have one central aspect in common: they are usually constituted by pre-trained models using generic data [36]. This is, for instance, the conventional method in AI-based solutions for the classification of users data in HAR systems [37,38] or processing health-related data [39,40]. Nevertheless, using pre-trained models in traditional ML approaches limits their performance and ability to adapt to end-users' needs, as transforming new data into useful information is complex [41,42]. Consequently, intelligent solutions usually raise questions about the accuracy of the collected data or how well that data can be associated with the phenomena it measures [43,44]. For example, users' perception of activity tracking devices is influenced by their expectations [45,46], which may lead to frustration or disengagement when the lack of knowledge on how their devices work, what data is collected, or how the measured phenomena are calculated, impair this perception [47,48]. Simultaneously, making humans part of the learning and decision-making process of a system can give them a sense of agency, which can encourage the collaboration with technology [49–51]. This was exemplified in a study by Dietvorst et al. [52], in which participants were able to modify an algorithm, and the researchers observed that their participation in the decision-making process resulted in greater satisfaction with the outcome. This highlights the importance of allowing the user greater control over the system's performance while increasing participation.

For this reason, the evolution of smart environments and systems should lean towards tighter user interaction. Under this context, IML emerges as an alternative to traditional ML techniques. IML proposes a collaborative approach that enables users to contribute to the automated process of intelligent systems and ML algorithms, improving them through feedback and allowing for flexible and rapid adaptation of smart solutions to new circumstances. Various applications, including predictive maintenance [53], design of smart spaces and cyber–physical systems [54,55], intelligent wearable robotics [56], medical diagnosis [57], or sentiment analysis [58], among others, have been developed based on the concept of collaboration between humans and machines. These applications are used in domains as varied as education [59], cyber-security [60], industry [61], or healthcare [62–64]. For instance, one illustrative example of the potential of IML in health applications is enabling the communication between the brain and external elements through brain computer interfaces [65]. With user feedback, systems like prosthetic devices, neurofeedback games, or applications for identifying and targeting visual objects can benefit from interaction to adjust their parameters, ultimately enhancing the user experience and performance [66,67]. These examples demonstrate how IML can optimize the learning behavior of these solutions through human–machine interactions.

In all these cases, IML models are designed to integrate human input into the ML solutions interactively, steering the supervised learning process of the model in different stages [68,69]. Thus, incorporating human expertise and knowledge and exploiting their strengths. Therefore, IML allows end-users to interact with the learning process to tune the system or feed it with more data [70]. This corresponds to HiTL approach that requires human intervention to create enhanced learning processes following a hybrid approach [71–74]. This concept is particularly relevant in HAR applications as, through interactive approaches, users can be involved in helping the learning system to improve its detection capabilities throughout time by providing feedback, in the form of correct labels, for some of the predictions the system makes [18,75]. Active Learning, a sub-field of IML, is a prominent example of the success of the HiTL paradigm, which incorporates user feedback in the learning process to give meaning to the most informative samples of the initial data [76–79]. Hence, users' collaboration with AI techniques can take many roles in those approaches, such as data curation, learning algorithm tuning, or labeling [80]. In this line, several authors settled on more participatory approaches, taking advantage of human knowledge and, more specifically, non-ML experts to build and improve ML solutions [81] using visual exploratory tools [62,82–84] and data analysis and interactive exploration approaches [85–87]. Furthermore, Smith et al. [88] studied this collaboration from a two-fold perspective. First, from the point of view of the ML model, addressing how systems can learn interactively from non-ML experts. Secondly, from the point of view of the user, concluding that appropriate tools to guide them in the process can enrich non-experts' experience.

According to previous statements, IML solutions should serve as a catalyst for fostering collaboration involving users in intelligent systems' learning process. This can lead to ongoing interactions that enhance their usefulness, accessibility, and usability for each unique individual (i.e., improving the classification capabilities of IA-models [35] or providing accurate just-in-time recommendations [89]). Nevertheless, to get this, it is important to improve ML models and consider the human-centered perspective of this collaboration and the human considerations of this interaction [90–92]. To this end, McCallum et al. [93] evaluated how users can be supported to contribute to improving a ML model and found that users have a low perception of their actions. Therefore, improving the interaction between humans and ML models is necessary to make the process more accessible and efficient [94]. This is aligned with integrating explanations into interactive ML models to develop a bi-directional communication channel between human stakeholders and intelligent systems [95,96].

In this regard, Human–Computer Interaction (HCI) plays a crucial role in promoting users' participation in the design, improvement, and dissemination of learning systems [97]. Vishwarupe et al. [98] emphasized the importance of a robust, transparent, ethical, intelligent, and interactive mechanism for the co-existence of AI and HCI systems, which could be the foundation of this collaboration. The user-centered design process is identified as a cornerstone aspect that can help develop a new paradigm for advancing technology by focusing on accessibility and user-friendliness. Furthermore, explainability, usability, and transparency are key areas of improvement for both traditional ML and IML systems [99,100]. As a result, the IML process should prioritize the user as the primary driver of an interactive bi-directional process to achieve the desired system behavior [101]. Empowering users to collaborate with intelligent systems is critical to ensure their interaction is effective [29]. In consequence, the barriers to collaboration need to be lowered [102], which involves ensuring adaptability. Adaptability is essential for collaboration to work efficiently and for human comfort and performance, as the success of the interaction depends on the ability of its members (the user and the system) to adapt their policies in a way that benefits the other [103]. Therefore, the system must continuously adapt and personalize its behavior based on the user's preferences to create a mutual adaptation phenomenon [34].

In parallel, user acceptance is also fundamental when it comes to involving the final user in participating in intelligent systems according to the HitL paradigm [27]. According to this last work, acceptance is related to involvement, which is key for this collaboration to occur. That is, users could be willing to use a specific system or technology (behavioral intention), but they may not necessarily have the same propensity to "cooperate" with the machine to give it feedback or contributions to improving it. For this reason, an effective system needs to engage the user in the task being performed to motivate them to achieve the desired outcomes of the collaboration [104]. Indeed, engagement can be seen as the goal of maintaining users' interactions, with may be aligned with the willingness to continue using the system [104,105], and refers to the degree of involvement, interaction, and emotional connection a user has with an intelligent system or technology [106]. From this perspective, Oertel et al. [107] reviewed previous efforts addressing the relevance of engagement. According to them, knowing the level of user engagement can be advantageous for customizing systems' behavior, as well as indicating the interaction's quality and the user's satisfaction with the system. Therefore, in the case of human–AI collaboration, user engagement also encompasses the level of communication and transparency that the user perceives from the AI system [108]. Thus, bringing closer the gap between automated systems and users that also has to do with understanding the level of trust users have in the decision-making process of the automated ML approach [109]. In fact, the lack of user trust may deter the user from following the suggestions of a system and be detrimental to the intelligent solution's uptake [110].

For this reason, it is essential to have a good trade-off between the efforts made, the perceived value of such efforts, and the trust in the behavior of intelligent systems. Under this context, the level of involvement needed for this collaboration appears to be a barrier to motivating the user to participate in model improvement over a long time, especially when there is no offset with the perceived value produced. For instance, in the experimental evaluation performed by Masson et al. [44] regarding users' involvement with AI systems, participants initially took an active role in data capture. However, most of them eventually quit because of the time involved, poor accuracy, and perceived reward. Based on that, continuously adapting the interactive system regarding users' current goals and involvement levels is pivotal when designing trustworthy solutions. Similarly, Ramos et al. [111] delved into their willingness to interact with the deployed system and determined that it may vary along with context and task, as well as the particularities of each individual.

In summary, the reviewed works demonstrate the advantages of including humans in the learning process of AI algorithms. While technological advances have paved the way for this interaction, we should not rush into it without carefully considering the human factors involved. The success of this collaboration relies on integrating the human element as an active decision-maker within the system. For this reason, from a user-centric point of view, the interest of IML lies in how this process can help humans to address how humans provide data, cope with inaccurate models, and what types or frequency of questions are appropriate to ask them [112]. To attain this goal, it is crucial to comprehensively examine the different dimensions of interaction, including communication, involvement, and adaptability, to gain deeper insight into their impact on user integration and engagement. Despite this, previous IML research has largely overlooked the challenges and hindrances arising from human factors such as stress, motivation, and fatigue, which can significantly affect their performance in collaboration [113]. Hence, it is necessary to consider its potential impact on the design process of intelligent solutions, as well as the individual and situational circumstances of users, to adapt the interaction requirements of the systems for their availability, participation and preferences. That is, to understand how people interact (and want to interact) with the ML system. For this reason, this work will consider the role of the user in interactive smart workplaces. Following the IML process decomposition presented by Porter et al. [85], we will focus on the training dialogue between users and IML solutions. More particularly, proposing customizable and flexible interaction techniques to meet the requirements and expectations of end-users in this dialogue.

3. The smart drink monitoring system

As previously presented, this work seeks to progress in setting up bi-directional channels to enable end-users' participation in the model training and fitting. To do so, user–machine interfaces and interaction mechanisms mediating between intelligent systems and end-users must be devised to provide feedback across the whole learning life cycle. Therefore, in this section, we present an interactive IoT-based smart system that will be used to evaluate users' opinions regarding human–machine collaboration in detecting hydration habits in the workplace. This prototype, coined as Smart Drink Monitoring System, is made up of two parts that are described in detail in the following two sub-sections: (i) an IoT-based device that monitors users' actions and provides quick feedback to them, and (ii) two graphical applications through which the user can customize the system, modulate their degree of involvement in the learning process, and provide new data examples to personalize the ML model.

Fig. 1 illustrates the interaction between the user (the human-in-the-loop), IoT device, User Management System, and Model Personalization Engine as part of the Smart Drink Monitoring System. On the one hand, the User Management System allows the user to define their usage preferences with the IoT device, including how often it can ask the user if it has correctly identified an activity. Additionally, the user can employ the Model Personalization Engine to record new examples of their data, which can be used to improve the model that classifies new data collected by the IoT device. On the other hand, the user interacts with the IoT device by validating the activities detected and classified by the model. If the model is uncertain about an activity, the IoT device will ask the user for confirmation. If the user has specified a limit on the number of times the IoT device can ask for confirmation, and that limit has been reached, the IoT device will make its best guess about the activity. This procedure and the characteristics of each part of the system will be explained in detail hereafter.

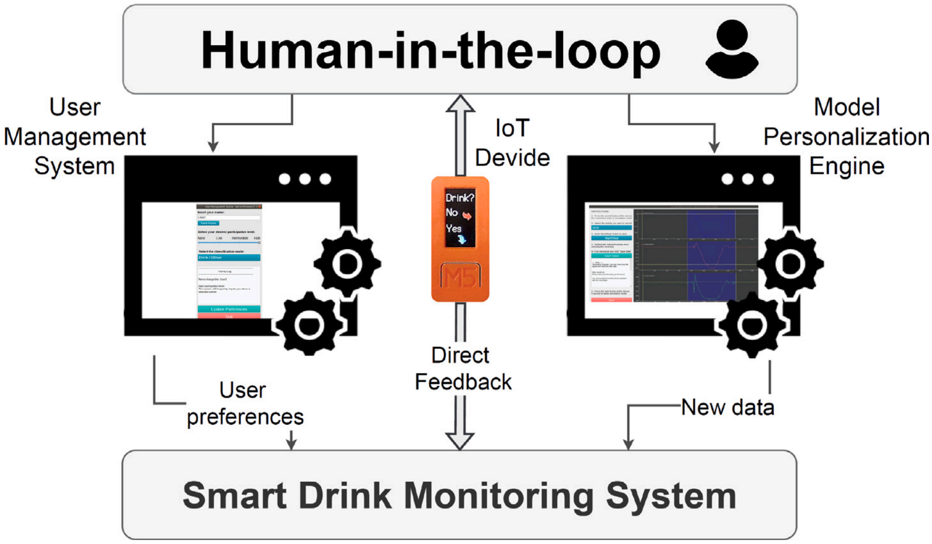

Fig. 1. Diagram of the human-in-the-loop system consisting of an IoT device, a User Management System, and a Model Personalization Engine. The end user interacts with all components, setting the interaction preferences and providing new label data to the monitoring system.

Fig. 2. A sample of the messages that can be prompted to a user when detecting a hydration activity through the device's display. As can be seen, in some cases, the drinking gesture is automatically detected, while, in case of uncertainty, the user must provide validation feedback to confirm the performed gesture.

3.1. The smart drink IoT device

As can be observed in Fig. 3, this orange IoT device can be fastened to any bottle, cup, or drink container. The device's primary function is to capture and log all user interactions with a liquid container, utilizing an embedded inertial sensor. Therefore, it is a practical example of how an everyday object can be augmented with technology to provide new functionalities, such as detecting people's hydration patterns. For this prototype, the commercial IoT development device M5-StickC was used.[1] Specifically, the inertial sensors of this IoT device register movement in terms of acceleration and orientation. When any motion is detected, the captured data is sent wirelessly to an Edge device (e.g., a Raspberry Pi device[2]), where it can be used to distinguish if a drinking gesture or any other movement has been detected.

The main characteristic of this device lies in its interactivity. Following the IML strategy, this device can prompt notifications or inquire the user about any movement detected through the built-in color LCD screen and buttons. An example of the range of messages that could be displayed on the LCD screen and the possibilities of the enabled interactions is included in Fig. 2. If the ML model classifies the captured data with high confidence as a hydration action, the user will receive a message informing them of the detection. However, if the system cannot predict the movement with the necessary confidence, the user will be prompted to confirm the gesture they have just performed. To respond to the YES/NO query, the user can use the built-in buttons (front for 'Yes' and lateral for 'No'). The response will be recorded and used for further model retraining stages.

1 https://docs.m5stack.com/en/core/m5stickc/
2 https://www.raspberrypi.org/

Fig. 3. The smart drink IoT Device .

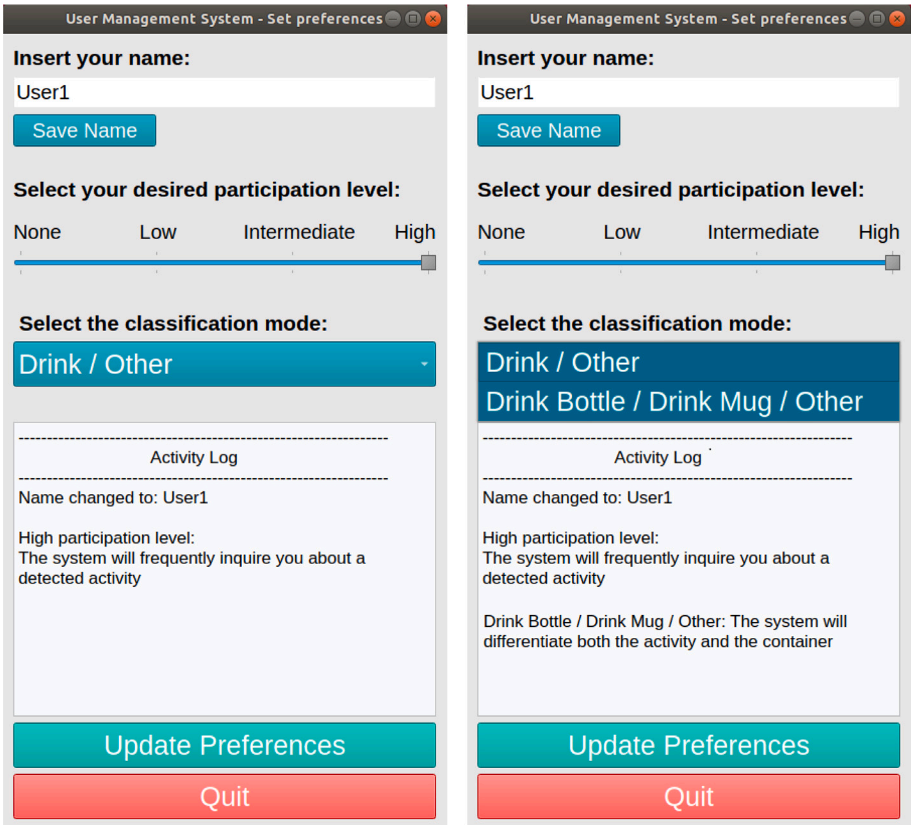

Fig. 4. The User Management System application is designed to set the system's preferences, including modulating the desired participation level and defining the classification mode (detecting only the drinking gesture or also detecting the container).

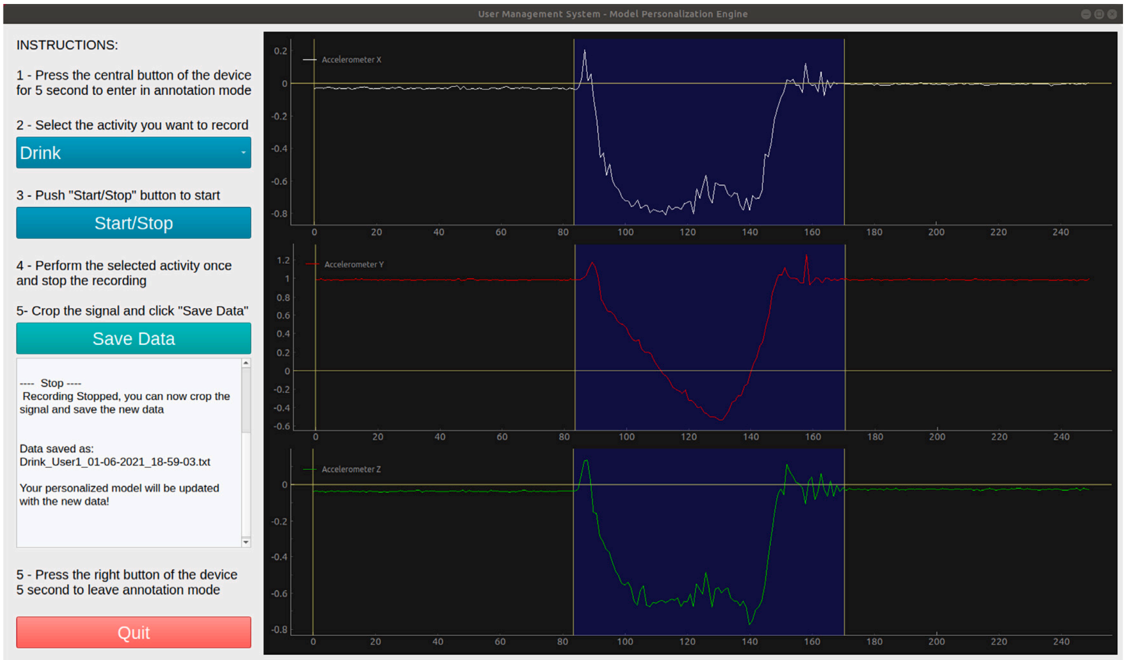

Fig. 5. The Model Personalization Engine application. Through this interface, users can record their examples of data and save them for further retraining processes of the model.

3.2. User management system and model personalization engine

The User Management System (Fig. 4) and the Model Personalization Engine (Fig. 5) are conceived as two GUI interfaces through which users can tailor the system and include their personalized examples of data in the model. These GUIs are expected to promote enhanced user interaction and voluntary participation, encouraging user adherence through bespoke adaptation.

On the one hand, the User Management System is the primary Cross-platform Desktop application in which end-users can customize the desired system preferences for the IoT device. To better fit a wider diversity of users, it is possible to define the desired level of participation in the proposed interactive scenario through this interface. Three levels of involvement are determined: *High*, *Intermediate* or *Low*, as can be seen in Fig. 4. This selection determines the frequency the IoT-based device may inquire the user about a specific activity performed. It also includes the *None* option, which eliminates the system functionality's interactive component. In this case, by selecting this option, the system becomes a non-interactive or classical ML approach with no user involvement in the learning process. Furthermore, it is possible to define whether the user wants the system to discern between the type of container used (e.g., a bottle or a cup/mug). This makes the classification options more flexible and adapts the system to the user's expectations. Users can always use the same type of container (for example, a bottle from which they always drink water) or vary between the bottle mentioned above and a cup or a mug (where they can drink tea or coffee). This is another example of the flexibility provided by the system to make it more robust for tailoring purposes. Finally, all the selected options are saved and associated with the user name. End users can revisit and update their preferences at any time.

On the other hand, the Model Personalization Engine is the second developed Cross-platform Desktop application designed to assist users in personalizing their classification model. Thanks to this interface, observed in Fig. 5, users can provide examples of their hydration movement patterns to retrain the model to match better their actual interaction with bottles or mugs. That is, they can begin recording and perform a specific movement, then select the corresponding segment of the recorded signal using a cropping sliding window feature and save this data as a new labeled example to personalize the baseline model. To enter the training mode, users need to hold down the front button of the IoT device for 5 s. The application displays real-time accelerometer signals captured by the inertial sensors when the user clicks on the button to record movements and prompts them to define the type of activity they want to personalize, such as the drinking activity shown in the figure, once the corresponding part of the signal is selected.

The concept of transparency and explainability of the ML process is embodied in this idea, as it provides users with a clear view of the data captured by the device. The accelerometer signals displayed on the screen are directly linked to the movements of the container, fostering a better understanding of how the system identifies activities based on signal patterns. This visual feedback reduces the risk of user disengagement caused by a lack of comprehension of the decision-making process, potentially increasing their trust and confidence in the system.

Table 1
Descriptive statistics of the demographic information of the participant subjects.

		N° of subjects	Percentage (%)
Gender	Male	7	58, 3
	Female	5	41, 7
Age group	<25	1	8, 33
	25–40	6	50, 0
	41–65	4	33, 3
Educational achievement	Post-graduate (MsC of eq.)	4	33, 3
	Doctoral degree (PhD)	8	66, 7

The source code for both tools is available in Github.[3]

4. Evaluation objectives, procedure, and methodology

As has been discussed, by using the interactive approach discussed earlier, users can collaborate with the system to customize activities and improve the model for better classification of activities in a workplace context. To evaluate the system's performance and usefulness from a user perspective, we conducted an experiment with various employees from a research center. In the following sections, we will describe the evaluation process and present the results. Before that, we revisit the evaluation objectives and research questions.

4.1. Evaluation objectives

The objective of this study is to gain an understanding of users' willingness to participate in the customization process of the ML-based system, as well as the most effective ways to motivate such interactions. To achieve this goal, two research questions were formulated based on the requirements identified in the existing literature on the customization and adaptation of IML systems.

Research Question 1: *Which is the user's willingness to be involved in obtaining more accurate predictions?*

According to Yang et al. [46], users are likely to expect to be able to customize a device to suit their individual needs better. A fine-tuning of the models by the end-users (e.g., through re-training and debugging of models/classifiers) may increase its performance. Moreover, including user-specific data also improves the detection capabilities of a ML for each user, helping to address a wider diversity of user profiles and expectations [114]. However, customizing a system can be a significant burden for some users if the collaboration is not presented appropriately. This research question aims to investigate whether users are willing to engage in customizing and improving a system, to what extent, and the motivations behind their involvement.

Research Question 2: *Which is considered a good trade-off effort between the improvements and the time commitment to help the system learn?*

Meyer et al. [115] state that there is a connection between the accuracy and reliability of data and the effort that users put into acquiring it and collaborating with the learning system. This effort requires a trade-off between the user's involvement and the potential improvement in the results. If the effort is deemed greater than the perceived value of the system and users do not receive tangible benefits, it may not be seen as rewarding [44]. In addition, the commitment to maintain this collaborative dynamic over time can become arduous for some users. Consequently, greater flexibility is needed to better adapt the interactive system to the context and the involvement level of every individual [116]. Therefore, our goal with this question is to gain a deeper understanding of the incentives that motivate users to remain committed over time and what they anticipate receiving in exchange. Additionally, we explore how the ability to adjust their participation level at any time is viewed as advantageous for increasing their engagement in the learning process.

4.2. Procedure

The study protocol involves various tasks performed in a controlled lab setting to introduce the participants to the interactive system. Subsequently, a semi-structured interview is conducted to gather insights into their experience gained through the process. A total of 12 participants were recruited through convenience sampling to participate in this study (7 men and 5 women). All 12 participants in the study are middle-aged, and 10 have jobs requiring moderate to high levels of interaction with information and communication technologies. Additionally, 5 of the participants have direct involvement with AI techniques and are familiar with the concept of IML. Table 1 provides an overview of the demographic profiles of the volunteers who participated in the present study. The sessions had a duration of 20 min and were conducted with audio recording enabled. Initially, the participants were introduced to the concept of IML, and the Smart Drink Monitoring System described in Section 3. The interviewer also explained each personalization option, such as the ability to determine the level of involvement according to their interest. Following that, participants were requested to perform sample interactions with a bottle equipped with the IoT device, as depicted in Fig. 3. These

[3] https://github.com/OihaneGomez/Smart_Drink_Monitoring

Table 2
The questions that were inquired to participants in different phases of the performed evaluation.

	Question
Q1	What is your perception of a device that can learn from you on a day-to-day basis and improve its performance?
Q2	Which level of participation do you think you would choose? What is your perception of the option to modulate your participation?
Q3	What would you consider an excessive frequency for the device to interact with you? Would you consider it intrusive, and could it interfere with your workday?
Q4	Do you think the interaction with the device is adequate to make the system adapt to you?. What other information or feedback would you like to receive to keep your collaboration with the device going?
Q5	Would you be willing to initially spend more time improving the system knowing that, down the road, you would have to perform fewer interactions?
Q6	Which of the two methods (the reactive or the proactive approach) suits the most to you and your routine?

interactions included a task to collect data to familiarize the users with the interactive features of the IoT system. Then, they were invited to explore the personalization preferences to demonstrate the broad spectrum of available options in the two GUI-based Desktop apps created. To obtain evaluative data, all data-gathering tools were operational (i.e., the system operated autonomously without human intervention). However, for those interactions that required identifying a particular gesture, a Wizard-of-Oz testing approach was followed to enhance the assessment's outcome [117]. In these Wizard-of-Oz tasks, the participants were immersed in several scenarios where they could interact with the developed system in a controlled manner directed by the session moderator.

The study examined two methods for the data sampling task: reactive and proactive. While participants had the opportunity to try both methods, they always began with the reactive approach. During the reactive approach, participants were asked to interact with the Smart Drink IoT device using simple mechanisms, such as pushing a button, to confirm the correct labeling for a specific hydration gesture once queried directly by the system. The User Management System was also presented, allowing participants to select their desired level of participation from four options: None, Low, Intermediate, or High. The levels of participation reflected the user's willingness and engagement in labeling new data instances, which corresponded to the frequency with which the device would prompt them to confirm or correct a recognized gesture. Next, the proactive approach was introduced. Participants were asked to record new data examples using the Model Personalization Engine to test it. This approach evaluated the participants' willingness to use a system that enabled them to provide examples proactively to customize the detection of activities (such as repeating a gesture or marking a starting position), thus assessing whether they were willing to voluntarily help the system to tune the ML model, without waiting for the system to prompt them to do so.

To prevent any learning bias during the interaction with the system, six out of the twelve participants were asked to set their desired data labeling preferences before being introduced to the Smart Drink IoT-based system (Intervention 1). In contrast, the remaining participants were asked to select their preferences after using the device (Intervention 2). Nonetheless, after interacting with the device and assessing the labeling tasks' required effort, the first group was allowed to change their initial decision. Throughout the experiment, participants were asked to respond to and discuss several questions regarding their perceptions and preferences about the system. These questions are included in Table 2 and were asked at different phases of the experiment, depending on whether the participants had set their involvement preferences before or after interacting with the IoT device (Intervention 1 vs Intervention 2). This allowed the researchers to collect participants' thoughts about the data-gathering mechanisms and their preferred interaction mode (reactive or proactive). Finally, at the end of the experiment, participants had the opportunity to make any additional comments.

5. Analysis and results

The main aim of analyzing the feedback provided by the participants is to assess their inclination towards involvement in customizing the interactive system and their preferred mode of interaction. Additionally, this intervention aims to gain insights into the users' perspectives on the flexibility offered to them in determining how and when to participate in the learning process of the hydration system. Finally, we also investigated whether participants intended to modify their initial perceptions of the proposed interactive scenario for the workplace.

To evaluate these three different aspects, the empirical findings of the experimental evaluation are organized around three overarching themes in this Section: (i) initial perceptions of the interactive system, (ii) involvement modulation and device feedback, and (iii) their opinions towards the proactive interactive strategy. The first two themes refer to the Smart Drink IoT Device (Fig. 2) and the Users Management System (Fig. 4), which involve the interaction with the device itself in accordance with the reactive approach and the possibility of changing the frequency of this interaction. For the third theme, the proactive approach was introduced through the Model Personalization Engine (Fig. 5) and compared to the previous interaction mechanism. Finally, the evaluation's main findings are summarized and analyzed in relation to the research questions introduced in the previous Section of this paper.

5.1. Initial perceptions of the interactive system

Following the description of the Smart Drink Monitoring System, participants were asked about their overall perception of the system. All participants expressed a positive or very positive attitude towards the possibility of interacting with it. In fact, participants particularly appreciated its adaptability and the idea of personalizing the recognition of activities. Some participants described their positive thoughts as positive because they were interested in the system recognizing their own hand movements. In this regard, they expressed no doubts about the system's performance and ability to learn from them. Thanks to the interactive capabilities described, one participant expressed confidence in the system's ability to learn from any user and adapt to their needs. This increased the perceived usefulness of the interactive prototype during the evaluation.

Participants who interacted with the Smart Drink IoT Device before the User Management Interface (interaction 1) oriented their initial opinions towards aspects related to the device's purpose or usability and less towards personalization. For instance, one participant found the device beneficial primarily because of its health-related purpose, while two participants emphasized their interest in using it on a daily basis at their desks or even bringing it to meetings, considering that the feedback mechanisms were not intrusive. As they were not yet familiar with the option to modulate their potential participation in the interactive proposal, the system's learning process raised doubts about an excessive inquiring frequency and/or the number of interactions needed to provide data to the system. For example, one participant found the idea of annotating new data interesting as long as it does not force users to do it every time a movement is detected or when they are busy with work-related tasks. Conversely, participants who were first introduced to the User Management Interface tended to focus more on the idea of modulating their level of participation and less on the device's usefulness or performance when forming their initial opinions. In fact, among all participants in this testing order, personalization and tailored interaction were among the most positively perceived characteristics of the system.

5.2. Involvement modulation and device's feedback

Participants demonstrated their positive perception towards the system's adaptability and personalization when they were presented with the option of setting their system's preferences through a GUI. This was in line with their initial impressions, as described in the previous sub-section, where they were interested in customizing and modulating their involvement level. Two participants even considered this option to be the most valuable characteristic of the system. Additionally, another participant expressed interest in the ability to change their involvement level at any time, while another suggested that they would like to have the option to modify this parameter constantly.

In order to gain more insight into the participants' eagerness to take part in the Smart Drink Monitoring System's learning process, they were prompted to select their preferred level of participation through the management interface of the Desktop app. The options presented were "None", "Low", "Intermediate", and "High", and participants were informed that these options would influence the frequency with which the IoT Device would request them to label a detected movement. The most popular choice was "Intermediate", selected by 7 participants. "High" was chosen by 3 participants, while "None" and "Low" were selected by one participant each. No clear pattern was observed when examining these responses based on the order of intervention (i.e., whether participants first interacted with the IoT device before being introduced to personalization features or vice versa). Participants who were asked to select their preferred level of involvement before using the Smart Drink IoT Device had the option to change their selection afterwards, but none of them did. This indicates that the functionality and usability of the device do not appear to depend on the level of involvement. This suggests that the functionality or usability of the device does not appear to be a dependent factor on the level of involvement.

It should be noted that participants who initially selected a high level of participation indicated that they may decrease their involvement over time depending on the system's response. In other words, highly motivated participants would be willing to collaborate with the system as much as possible at the beginning but gradually decrease their involvement once the system has enough data to learn from them. Some participants who chose the intermediate level did so because they wanted to wait and see how much burden daily interaction with the system would entail. In contrast, the participant who selected a low level of involvement stated that they did not want to be prompted more than twice a day. However, despite this initial reluctance, they were in favor of having the option to customize this setting at any time. The participant who selected "None" stated that they did not find the device's way of interacting or receiving notifications intrusive but did not like notifications of any kind during the workday. In this line, two other participants echoed the same opinion mentioned earlier about the system's feedback and how intrusive it may be if this interaction is not calibrated correctly. One of them emphasized that they did not want to feel obligated to always respond to the system's prompts. For this reason, they consider the possibility of modulating this frequency a positive feature. On the other hand, the remaining participants believed that how the system interacts with them, which involves on-screen notifications with the built-in LCD and device buttons to respond, was an appropriate mechanism and not intrusive. Additionally, two participants argued that the system's queries did not distract them from their work tasks since they could easily integrate them into their hydration routine of raising their hands, holding a bottle/mug, drinking, and placing the container back on the desk.

5.3. The proactive interactive strategy

When presented with the option, most participants expressed their interest in using the Model Personalization Engine's feature to record new data samples and improve the model. Only two users showed indifference to this feature. One of them stated that they had too many tasks to do at work and did not want to spend any extra time on this feature. The other one claimed that they did not want to make any additional effort apart from their daily tasks at work. In this case, both participants preferred the reactive interaction through the IoT device over using an application to record more examples of data specifically. On the other hand, among the participants willing to use this self-reporting application, two preferred the reactive approach as it suited their routine better but were still open to using the application if required. Table 3 details the opinions of each subject participating in the experiment

Table 3
Detailed information on the responses of each subject regarding their initial level of involvement, whether they would change it after interacting with the system in the case of Intervention 2, and their preferred approach for labeling new data.

Subject	Intervention	Initial involvement	Would you maintain this level?	Approach
1	2	High	–	Proactive
2	2	Intermediate	–	Proactive
3	2	Intermediate	–	Reactive
4	1	Intermediate	Yes	Proactive
5	1	High	Yes	Proactive
6	1	Low	Yes	Reactive
7	2	None	–	Proactive
8	1	High	Yes	Proactive
9	1	Intermediate	Yes	Reactive
10	2	Intermediate	–	Proactive
11	2	Intermediate	–	Reactive
12	1	Intermediate	Yes	Proactive

on their envisaged level of involvement and the preferred interactive mechanism (reactive vs proactive). It also includes whether the current level of involvement should be maintained in the case of Intervention 1 (those who set their involvement preferences before being introduced to the whole system).

Those results reveal a significant variation in the optimal interaction method for data labeling, being the proactive approach the most selected one (8 vs 4). The underlying reasons for these different preferences are diverse and the opinion towards choosing among different methods was positive. For instance, one participant remarked that it was reasonable for each individual to have a different perspective and appreciated the flexibility of selecting from various interactive methods. In fact, even though some participants exhibited favoritism towards a particular method, many indicated their readiness to utilize both methods in conjunction or alternate between them as needed. Several participants unanimously preferred to provide more examples during the early stages of the learning process and fewer during subsequent use. Those eager to contribute more examples at the beginning stated that they would continue to use the reactive method and engage with the IoT device over time. In other words, some participants mentioned that they would prefer to use the proactive approach initially to create a personalized database of examples to train the model. Then, they would continue contributing to this collection of samples collaboratively to continue improving it. Another argument in favor of the Model Personalization Engine was the ease of use of this proactive approach. As one participant emphasized, recording examples of data only requires a moment and can be done multiple times whenever someone has a spare moment. Furthermore, one participant justified selecting the proactive approach as they were keen to learn more about the system's operations.

Besides, suggestions for improving the proactive data annotation process were brought up by some participants. One recommendation was to simplify the self-annotation process, as it may appear too complicated to some users and discourage them from using it. This sentiment was echoed by another participant who agreed that the annotation mechanism could be less user-friendly for some individuals, potentially causing them to opt out of annotating gesture data. As a solution, these participants proposed incorporating gamification elements to make the process more engaging and motivate end-users to continue collaborating over time.

5.4. Summary of findings

The main findings of the conducted evaluation are summarized in Table 4. Participants generally reported a positive user experience after trying out the smart system for the first time. Additionally, participants were overall interested in the final purpose of the recognition system. Thus, they saw an added value in the health-related problem that the presented use-case through an IoT device aimed to tackle. Therefore, we argue that both the positive experience and the health-related purpose helped attract their interest in the joint-learning scenario that the system enables. Finally, participants reported high satisfaction levels about the possibility of modulating the desired participation degree. This flexibility stands out as one of the most highlighted characteristics of the introduced system to ensure its long-lasting use, as is explained next.

5.4.1. Interaction modality and desired level of involvement

The participants' initial level of interest in the learning process of the IoT device was generally moderate to high. They expressed their willingness to assist in either labeling detected gestures (reactive approach) or providing new personal data to help the system learn faster (proactive approach). Generating end-user data to improve the activity detection system's outcome was more attractive to them than the reactive scenario, as shown on the left side of Fig. 6. As a result, 66% of the participants found the proactive approach more suitable for their routine. Moreover, those willing to provide initial data input to the system proactively were also willing to continue collaborating with the system through the reactive method. They regarded the proactive strategy as an excellent way to expedite the learning process, intending to reduce their participation once they saw an improvement in its detection capabilities.

A variety of viewpoints were uncovered when assessing the degree of involvement of participants in the interactive learning process using the IoT Device. As illustrated on the right side of Fig. 6, the majority of participants (7 out of 12) favored the intermediate option, which allowed them to first observe how much feedback was needed before deciding on their final level of

Table 4
Summary of the main findings and results from the conducted evaluation highlighting participant preferences for system customization, involvement level, and self-reporting data in the study.

Category	Summary
System customization	Participants highly value the option to customize and modulate their involvement level, with two participants considering it the most valuable characteristic of the system. They want the option to change their involvement level at any time.
Involvement level	The most common desired involvement level among participants was "Intermediate" (7), followed by "High" (3), "None" (1) and "Low" (1). There was no clear pattern in responses based on the type of intervention carried out. Highly motivated participants wanted to collaborate as much as possible initially, but were willing to decrease involvement once the system had enough data.
Self-recorded data	Most participants were more interested in using the Model Personalization Engine to record new data samples to retrain the model (8 vs 4). Participants willing to use this self-training method opted to provide initial data to the system proactively instead of waiting for the system to ask them to do so.

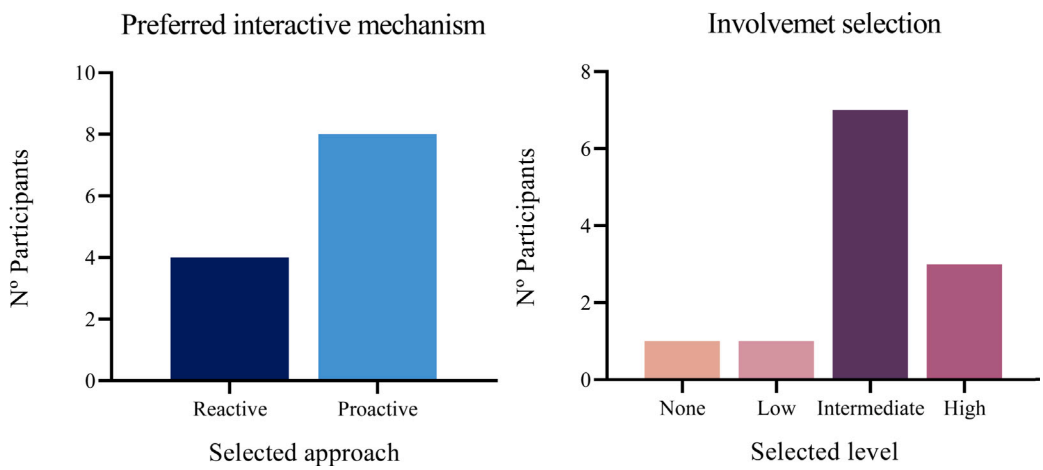

Fig. 6. Participants' responses when inquired about their preferred interactive modality (left) and involvement level in the interactive learning process (right).

involvement in providing feedback to the system regarding its performance in the classification task. Three participants were highly motivated to give this feedback, while the remaining two were less enthusiastic about this level of participation and leaned towards a less or even a non-interaction. The diverse range of opinions highlights the significance of enabling users to tailor the system to their own preferences and daily routines. This customization enhances the perceived utility of the technological solution and potentially prevents future disengagement, as users can modify the system's functionality to suit their own context and evolving feelings towards the system.

5.5. Limitations

To conclude this section on analysis and results, it is necessary to report the limitations detected in the study. Firstly, the qualitative opinions analyzed in this study were limited to the participants' initial thoughts when the system was introduced to them. Therefore, these findings cannot be extrapolated to determine how the proposed system would be adopted over an extended period. Instead, they can only serve as an initial indicator of the participants' predisposition towards the system. Secondly, the sample size in this study is not large enough to represent a diverse population of users. The participants were all between the ages of 20 and 65. It should also be noted that the majority of the participants in this study reported being comfortable with technology and possessing technical knowledge, including some familiarity with AI techniques. This could have potentially biased the results towards a more positive attitude towards the proposed system. Therefore, the findings of this study may not be generalizable to a broader population with less technical knowledge and experience. Another limitation of this study is the laboratory setting, which may not fully represent the real-world conditions in which the system would be used. Finally, we suggest that future research is necessary to gain a better understanding of how employees would like to participate in the collaborative scenario proposed by this interactive system.

6. Discussion

As has been observed through the manuscript, HitL and IML approaches combine the capabilities of human intelligence with computational intelligence to tackle complex problems in intelligent systems. Under this scope, HitL provides several advantages in terms of system performance. Firstly, allowing humans to provide feedback ensures accuracy and enables error correction in situations where the data is noisy, sparse, or ambiguous. Secondly, interactive approaches may improve efficiency by allowing users to assist ML models in focusing on relevant or informative data, thus reducing the amount of data that needs processing or labeling. Finally, HitL may enhance adaptability by enabling humans to assist intelligent systems in adjusting to changing conditions, preferences, or goals, which can increase the robustness and personalization of the system.

Nevertheless, the involvement of humans in the loop highlights the need for appropriate participatory mechanisms to manage their interactions with intelligent systems. Consequently, IML systems, such as the one presented in this manuscript, must prioritize the user's role in creating engaging scenarios that improve both the system's classification capabilities and the user's involvement. While these characteristics are always valuable in every interactive system, they become essential in the workplace context, where intelligent solutions can be seen as distracting if they are too intrusive. As a result, different end-users may have varying expectations and motivations when it comes to adapting and personalizing the system during the training and validation of HAR models. Hence, end-users should be entitled to provide feedback to the system to personalize it to their preferences at any time. In essence, "*one-size-fits-all*" solutions would not be sufficient enough for engaging end-users in long-lasting interactions with smart systems, as observed in the results provided in the previous section. Therefore, the challenge is to provide intelligent solutions that are flexible enough to meet different users' needs and expectations while understanding their willingness to help the system learn.

During the system's evaluation and in response to this article's defined first research question (*Which is the user's willingness to be involved in obtaining more accurate predictions?*), we investigated how participants viewed their role and willingness to engage in collaborative learning through an interactive IoT-based prototype specifically designed for use in a workplace setting. In this regard, participants expressed a high desire to participate in the system's learning process. That is, they reported a positive attitude towards improving the system's classification results with their data. Moreover, they highly valued the flexibility to customize their collaboration with the system according to their preferences and daily routine, which was the most significant characteristic among all the other determinants gathered. These customization capabilities enable the possibility of defining how much every individual wants to be involved in the process, aimed at adapting to most of the system's functionality to their needs. According to Mugge et al. [118], by personalizing a product or service, users direct time, energy, and attention to it. In this sense, users can create custom solutions they feel more attached to and conserve a sense of continuous novelty and technology appropriation [119]. This latter feature is crucial to increasing the system's perceived usefulness over time and preventing disengagement. According to technology appropriation theory, involving users in maintaining and improving digital strategies is essential to enhancing self-efficacy and satisfaction. Therefore, allowing individuals to participate in the learning process can foster a sense of psychological ownership of digital technology, where users feel like they have personalized the system according to their preferences.

To examine the participants' willingness to dedicate their time and effort to the learning process (as defined in research question 2: "What is considered a good trade-off between effort and improvements when helping the system learn?"), we analyzed two separate methods: reactive and proactive, for providing new data to the system. The reactive one was integrated into the interaction mechanism of the Smart Drink IoT Device (reactive). The other one explicitly involved recording new data samples using the available software tool (proactively), i.e., the Model Personalization Engine. Although participants showed some division of preferences, most were likely to spend their time voluntarily providing new data samples to the system. Following such a commitment, they expected to improve its detection capabilities more rapidly and reduce the number of interactions afterwards. Nevertheless, even after this initial effort, they continued to agree with responding to the system's interactions as long as the frequency of those interactions was progressively reduced. In this sense, this study revealed that participants are primarily satisfied with adapting the system to their needs. Moreover, this collaboration is extended to create a continuous and lasting interaction with the smart system, which may be the objective of many scholars working on adopting emerging technologies. With this collaboration, users are included in the control loop and iteratively help the system create personalized models adapted to their particularities on the fly. Hence, this joint action can improve both the model's performance and the user's confidence in the intelligent system [112], which is a relevant aspect of human-centric solutions designed for the workplace [120]. At the same time, an improvement of the user experience is required to achieve the actual settlement of IoT systems and intelligent solutions in our society [121]. Therefore, end-users expectations and their role in participatory approaches are pivotal factors when planning interactive strategies requiring additional user involvement. On this subject, we propose conceiving flexible solutions according to those expectations to fit better the needs of every individual that populates smart environments, particularly smart workplaces.

In summary, to address the gap in the literature that is often indifferent to human aspects in the design of collaborative intelligent systems and HitL approaches, this study aimed to explore the potential of IML solutions in the workplace context. While the results obtained are promising and emphasize the importance of user involvement in the training and validation processes, there are certain limitations to consider. Firstly, the relatively small sample size used in this study may affect the generalization of the results. Secondly, the study focused on a specific use case, and further research is necessary to evaluate the effectiveness of IML solutions in different scenarios and domains. Despite these limitations, this study provides valuable insights into the potential of IML solutions to create engaging and human-centric smart environments. The results emphasize the significance of user involvement and customization capabilities in increasing user satisfaction and engagement with intelligent systems. Overall, our study contributes to highlighting the importance of understanding the human factors that drive the interaction between users and technology and sheds light on how these factors could be applied to validation and data labeling in hybrid approaches and intelligent systems. In light of these insights, we encourage more research on this topic to improve the design and development of IML solutions that better meet the needs and expectations of end-users in different contexts.

7. Conclusions and future work

This work explored users' requirements and readiness to participate in IML solutions and presented a system (in the form of proof of concept) that introduces those ideas. This approach was evaluated using an IoT-based prototype, called The Smart Drink Monitoring System, which is a hydration monitoring system designed to classify office employees' hydration patterns. The prototype comprises an IoT smart device and two Desktop applications that allow users to customize the system, modulate their degree of involvement, and create new data samples to personalize a HAR model based on their data. The results of the in-lab evaluation performed showed that the interactive approach was favorable, with users finding value in customizing the system and improving detection rates using their own data. The ability to define their involvement level was also seen as a valuable aspect of the prototype. These findings emphasized the importance of designing flexible interactive systems that can adapt to end-users' preferences and particular needs, while also considering the extent to which users are willing to participate in the learning process. Despite the limitations of the study, the results of this intervention provide insights into developing more adaptable HitL approaches that promote collaboration between humans and machines. Thus, addressing the need for prioritizing user involvement, personalization and flexibility as relevant factors for further research and development in this area. Future work points to evaluating the presented solution in a real-world environment to quantitatively assess the metrics and data obtained and validate the insights gained in this study. That is, to continue progressing towards promoting a human-centered approach to HitL, making intelligent systems more interactive, inclusive, engaging and adaptive, and contributing to leveraging IML as a powerful tool for driving innovation across a wide range of fields and settings. This work represents a valuable initial step in this direction.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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