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The Human Factors of AI-Empowered Knowledge Sharing

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ABSTRACT

Many industries are facing the challenge of how to capture workers' knowledge such that it can be shared, in particular tacit knowledge. The operation of complex systems such as a manufacturing line is knowledge-intensive, especially if the operator must frequently reconfigure it for different products. Considering the breadth and dynamic nature of this knowledge, existing solutions for sharing knowledge (e.g., word-of-mouth, issue reports, document creation, and decision support systems) are inefficient and/or resource-intensive. Conversational user interfaces are an efficient way to convey information that mimics the way humans share knowledge; however, we know little about how to design them specifically for this purpose, especially regarding tacit knowledge. In this work, my main goal is to investigate how a cognitive assistant can be designed to facilitate (tacit) knowledge transfer between users of dynamic complex systems. I aim to achieve this by outlining the design requirements, challenges, and opportunities in factories; by collaboratively designing, implementing, and evaluating a cognitive assistant for sharing knowledge; studying the effects of design characteristics on aspects such as user experience; and finally, creating a set of design guidelines.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **Interactive systems and tools**; **Natural language interfaces**.

KEYWORDS

cognitive assistant, chatbots, industry 5.0, human-centred AI, knowledge sharing

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1 INTRODUCTION

Operating a complex system, such as an agile production line, is a knowledge-intensive task. A single operator may need to configure, optimize, and maintain a system that consists of more than a dozen machines for more than a hundred different products. Over time, operators learn the intricacies of their production line and how to optimally tune the system for each product and quickly fix issues. This is not simply a matter of entering the best parameters every time, as there are many contextual factors, for example, ambient temperature and the quality of raw products, that affect the system. In addition, the introduction of new products, the adjustment of existing ones, or changes in the mechanical systems result in highly dynamic best practices. As such, any system designed to support knowledge sharing should be able to dynamically update its knowledge base and associate it with contextual factors. Currently, training and knowledge sharing occurs through human-to-human interaction in industrial settings, that relies on extended 1-on-1 interaction. As a result, training new operators is highly resource-intensive [42]. Furthermore, it might take months before two operators have the opportunity to share their knowledge about a specific topic, and if one leaves, they take a lot of their valuable (tacit) knowledge with them. Experts can create instructional material for later consumption; however, our investigations in factories revealed that this material is rapidly out of date, difficult to access and maintain, and thus rarely used. Issue reports or shift reports are another, usually more up-to-date source of knowledge; however, they are often of poor quality or illegible recorded and therefore not useful [14]. An ubiquitous cognitive assistant with a conversational user interface could serve as an intermediary in the sharing of knowledge between operators. Unlike human colleagues, it is always available and, therefore, acquires and shares knowledge at scale.

My research goal is to investigate how to design a cognitive assistant that facilitates the transfer of (tacit) knowledge between operators of complex systems. In doing so, I will improve knowledge sharing regarding complex systems and advance the possibilities for successful human-AI collaborations in professional contexts. To accomplish this, the main objectives of my Ph.D. are as follows:

(1) Define requirements, opportunities, and challenges for knowledge sharing cognitive assistant in the context of agile manufacturing.
(2) Design, implement, and evaluate an cognitive assistant for knowledge sharing in the context of agile manufacturing.
(3) Map the impact of design characteristics (e.g., modality, proactivity, conversation style) on aspects such as user experience, task performance, cognitive load, knowledge sharing, and learning outcomes.
(4) Create design guidelines for cognitive assistants that share knowledge.

To achieve the objectives listed above, we performed a context analysis of agile manufacturing operators that included *semi-structured interviews*, a *thematic analysis* of problem descriptions, and *collaborative design* sessions. To get the full picture, we collected information from the operators themselves, but also from the perspective of their team leaders, maintenance personnel, managers,

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process engineers, quality control, and factory directors. *Literature reviews* were used to inform the design of the cognitive assistant. We conducted *usability studies* to improve our cognitive assistants in preparation for user studies. Furthermore, we use qualitative methods, such as *content analysis*, to identify areas for improvement. We use *comparative user studies* to evaluate our system compared to the current situation in factories and the effect of design characteristics (e.g., modality) on aspects such as *user experience* (UX), operator performance, and knowledge retention. Here, we make use of both subjective measures (e.g., user experience questionnaire (UEQ)) and objective measures (e.g., task duration and *physiological measurements*). We conduct *lab studies* where we can control more variables and achieve a higher number of participants. In addition, we conduct user studies in situ when possible (i.e., in factories) for *ecological validity*. We plan to use *crowd-sourcing* for large-scale online studies when we examine a large number of design characteristics in parallel or those with more subtle effects. Finally, our objective is to create design guidelines by consolidating the findings in our studies, organize *workshops*, and perform a *systematic literature review* of AI-empowered knowledge sharing.

2 BACKGROUND

Many industries face challenges in sharing knowledge between workers, especially tacit knowledge. Inherently, tacit knowledge is implicit, making it more difficult for individuals and companies to acquire and disseminate it [18]. Workers acquire tacit knowledge on the job to overcome the challenges of agile manufacturing. However, tacit knowledge is rarely generalized, explained, or formalized. Although several definitions of tacit knowledge state that it cannot be expressed verbally, Nonaka and Takeuchi [35] suggest that it can be divided into inexpressible and expressible types. This categorization indicates that tacit knowledge has multiple dimensions related to the ability to express it in words, formulas, trade secrets, rules of thumb, and tricks [33]. Recent studies of tacit knowledge in manufacturing have shown the enormous value that tacit knowledge holds [20]. Now we know that tacit knowledge can be converted into explicit knowledge and that they exist on a continuum [36]. Despite this, it remains resource intensive to collect and share. Researchers have manually acquired tacit knowledge through human motion capture, videos, and field interviews with experts and beginners in the manufacturing industry [17] – a process that requires skilled analysts. If data is available that details the actions of workers, data analysis techniques can be used to identify tacit knowledge [39],[46]. However, these techniques do not enable the knowledge holder to describe the reasoning behind their actions or add additional details, as an expert might when teaching a novice. To solve some of these challenges, a cognitive assistant could facilitate the sharing of tacit knowledge in a factory through dialectic interactions [15]. To our knowledge, no existing AI system has demonstrated the ability to collect and share tacit knowledge in agile manufacturing settings.

Whereas manufacturing automation has focused on replacing humans, we are now entering a new phase in which intelligent systems will fully merge with the physical world in cooperation with human intelligence [34]. Industrial applications for conversational agents—similar to Alexa, Google Assistant, or Siri—are an emerging research topic. Several AI assistants have emerged in different research communities with different names (e.g., digital assistants, software robots, or just chatbots). AI assistants can have significant benefits in manufacturing [48]. These include, for instance, central access to heterogeneous information systems, the delegation of tasks, and providing ubiquitous decision support [4, 40]. Using a voice-based conversational user interface (CUI) allows workers to keep their hands and eyes free to work on the machines. Furthermore, studies in the automotive context have shown positive effects of the use of CUIs on aspects such as cognitive demands/workload and environmental participation [27]. They can support workers in predictive maintenance [47] and augmented data analytics in manufacturing [49]. Longo et al. demonstrated an AI assistant integrated into an augmented reality application to train machine operators [31]. Their prototype provides information about safety measures, potential hazards, machine status and operations, and quality control procedures. Besides, it instructs users on lubrication, greasing, cleaning, checking, and restoring hydraulic pressure or fluids for maintenance. Rabelo, Romero and Zambiasi demonstrated how software robots, a concept overlapping with AI assistants, can assist operators [37]. They extended their solution so it can evaluate shop-floor information, identify production problems, assess operations performance, and use business analytics to support decision-making [3, 38]. Listl, Fischer, and Weyrich described an AI assistant connected to a plant simulation tool [30]. Their demonstrator allows users to adjust simulation parameters, model topology, and schedules. However, these systems are mainly based on predefined knowledge bases that require a lot of resources to create and maintain [13].

In an effort to bootstrap the population of knowledge bases, previous research has explored natural language processing (NLP) on existing maintenance reports to automatically discover knowledge, but numerous data quality issues were found [14]. Others concluded that technicians often describe problems informally, leading to inconsistencies and inaccuracies in the data; certain maintenance data, such as the actual root cause of a problem, are not always collected; and once the data is collected, it is often not used for future diagnosis [41]. Clearly, the poor quality of reports inhibits (AI-facilitated) knowledge sharing among technicians. CUIs have been shown to be a viable alternative to creating reports on paper or with graphical user interfaces, for example, voice-based CUIs are increasingly prevalent in the healthcare domain to support clinical workflows [32, 44]. CUIs in healthcare relieve physicians of the burden of documentation by using a digital scribe [11, 43]. In fact, CUIs have a positive impact on the accuracy and productivity of documentation [21]. Giving a verbal description of your actions and thoughts is intuitive, and designers use CUIs to better understand the user's thought process [12, 29].

A cognitive assistant is a smart system designed to "augment human intellect" by endowing one with cognitive capacities beyond what is humanly possible. Cognitive assistants have been found to reduce cognitive load when making decisions and taking actions [1, 6, 28]. By continuously learning from workers' experiences, cognitive assistants are able to adapt to changing physical environments, dynamic social contexts, and user needs [1]. Kimani et al. proposed an cognitive assistant called Amber that uses a sensing framework that could record users' faces, speech, and app usage in order to aid users with job prioritization, provide reminders, and inhibit social media diversions [25]. Natural language mechanism and context awareness could also enable cognitive assistants to efficiently acquire high-quality (tacit) knowledge shared by experienced workers and pass it on to novices [22]. Unlike systems designed to replace humans in specific tasks (e.g., industrial robots), cognitive assistants strive to complement human abilities to accomplish complex tasks, such as aiding life-long education and machine operation [1, 2, 28]. In addition, such assistants often outperform human capacities for communication and memory in a variety of ways, such as simultaneously providing dependable and repeatable communication between numerous users [1, 2]. To achieve the aims mentioned above, cognitive assistants should support efficient human-machine interfacing via natural language processing, interpretation of gestures, perception, vision, and sounds, augmented reality to provide additional layers of information, and others [1, 2]. Furthermore, advances in context awareness make it possible to improve a cognitive assistant's usefulness. For example, acquiring more accurate knowledge about city locations by asking questions when users are there [7] or inferring context from user utterances to provide more relevant tourist recommendations [10].

Researchers have recently made great progress in efficiently building and maintaining knowledge bases for AI systems [9], for example, by crowd-sourcing the process [26], extracting knowledge from online forums [19], and interactively learning from users [7]. All of the above solutions show promise and could be integrated into one system. However, knowledge cannot be reduced to simple rules. As Davenport and Prusak (1998) define it, "*knowledge is a fluid mix of framed experience, values, contextual information, and expert insights that provide a framework for evaluating and incorporating new experiences and information. It originates in and is applied in the minds of knowers* [8]." In addition, it is difficult to understand the user's experience (UX), impressions and values without interacting with the user, for example, via a CUI [45]. To our knowledge, no existing solution has ever acquired (tacit) operator knowledge to structure it, store it, and share it again with others in real time and on the shop floor.

3 PRELIMINARY RESULTS

As a result of literature review, context analysis, and co-design, we designed and implemented a cognitive assistant for agile manufacturing operators in mid-2022. In the accompanying article, we describe its architecture, user interaction scenarios, and discuss the opportunities and challenges we face [24]. In addition to presenting the challenges, we also outline how we tackle them, such as using context awareness to overcome the shortcomings of NLP to convey precise information quickly and using user feedback to maintain an ever-growing knowledge base.

We conducted a lab study ($N = 24$) to evaluate the use of a (voice) conversational user interface (CUI) to create maintenance reports using a Technology Probe [5]. We compare two groups that change the inner tube of a bicycle and report their work. Participants in one condition report their work during the task by voice, while the other group writes a report on paper afterward. We measure the duration of tasks, perceived workload, and the quality of reports. Overall, report quality was significantly in favor of the "CUI" group/condition. Interestingly, CUI-based reporting was not found to affect maintenance task completion time. In fact, the time to change the inner tube did not differ significantly between the two conditions ("CUI" and "Paper"). When reporting time is factored in, using a CUI can save technicians and their firms a significant amount of time. Clearly, the ability to report by voice during the maintenance task, rather than afterward, was the reason. Surprisingly, the overall perceived workload did not differ significantly between the "CUI" and "Paper" conditions. However, the perceived temporal demand for the "CUI" group was reported as significantly higher than that for the "Paper" group. The significance of this finding should be noted, as it suggests that designers of conversational systems for on-the-job knowledge acquisition should adjust conversational flow to task progress.

In another study, we explored one of the major challenges in acquiring knowledge from humans using a natural language interface, namely, how to reliably process precise domain-specific information [16]. We realized that it would be impossible to train the NLP model to understand all possible user utterances immediately. As such, conversation breakdowns are inevitable; however, each breakdown is also a learning opportunity to improve. Therefore, we explored user preferences regarding whose responsibility it is to learn from conversation breakdowns; namely, the user, the cognitive assistant, or both. We recruited 26 factory workers and compared user preferences for different learning mechanisms. Our result showed that users prefer to share the learning burden with the CA (61.3%), followed by completely outsourcing the learning burden to the CA (60.7%) as opposed to themselves.

Recently, we conducted a user study with 83 participants who performed eight knowledge exchange tasks with a cognitive assistant, completed a survey, and provided qualitative feedback [23]. Our results provide a deeper understanding of how prior training, context expertise, and interaction modality affect the user experience of cognitive assistants. We draw on our results to create design and evaluation guidelines for cognitive assistants that support knowledge exchange in fast-paced and demanding environments, such as an agile production line.

4 NEXT STEPS

Our next study will investigate the effect of using a cognitive assistant for knowledge sharing on task performance, knowledge retention, cognitive load, and user experience. We have created a simulated agile production line environment to perform this in a controlled laboratory environment. In addition to the objectives mentioned above, we will investigate several ways of prompting end-users to elicit (tacit) knowledge through conversational AI. In parallel, our goal is to run a crowd-sourced study to study the effect of several design characteristics (e.g., emoji use and explainable AI) on the trustworthiness and engagement with cognitive assistants for knowledge sharing. Lastly, we will perform usability studies of two assistant systems in the wild. When conducting studies in the wild, we must be careful not to negatively affect the production performance or safety of factory workers. Furthermore, we must be aware of ethical concerns, such as power imbalances between managers and workers, the collection of personal data (e.g., related to work performance) and how an individual's knowledge is a valuable asset to them, as well as their employer.

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