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A Cognitive Assistant for Operators: AI-Powered Knowledge Sharing on Complex Systems

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Operating a complex and dynamic system, such as an agile manufacturing line, is a knowledge-intensive task. It imposes a steep learning curve on novice operators and prompts experienced operators to continuously discover new knowledge, share it, and retain it. In practice, training novices is resource-intensive, and the knowledge discovered by experts is not shared effectively. To tackle these challenges, we developed an AI-powered pervasive system that provides cognitive augmentation to users of complex systems. We present an AI cognitive assistant that provides on-the-job training to novices while acquiring and sharing (tacit) knowledge from experts. Cognitive support is provided as dialectic recommendations for standard work instructions, decision-making, training material, and knowledge acquisition. These recommendations are adjusted to the user and context to minimize interruption and maximize relevance. In this article, we describe how we implemented the cognitive assistant, how it interacts with users, its usage scenarios, and the challenges and opportunities.

Agile manufacturing is driven by the proliferation of product customization and on-demand production. Although it enables manufacturers to build high-standard, consumer-based products and respond to varying demands, it requires highly skilled personnel to operate agile production lines. To keep up with continuously changing production demands, cope with fluid product requirements, and intense information-processing, production-line operators need to adopt a working approach that welcomes change. Operators should be empowered to perform transparent customization, allowing rapid adaptations, providing operational flexibility, while continuously enhancing their skills.

One of the challenges that many industries face is the sharing of knowledge among workers, most notably tacit knowledge. Inherently, tacit knowledge is implicit and not codified, making it harder for individuals and firms to capture and assimilate.[1] Workers acquire tacit knowledge in their line of work to face the challenges of agile manufacturing. This tacit knowledge is hardly generalized, explained, or formalized for the standardization of manufacturing operations and for the training of novice operators. Although many definitions of tacit knowledge state that it cannot be verbally expressed, Nonaka and Takeuchi[2] consider that tacit knowledge can be subdivided into inexpressible tacit knowledge and expressible tacit knowledge. This categorization suggests that tacit knowledge has multiple dimensions in relation to the ability to articulate it into words, recipes and formulas, trade secrets, rules of thumb, and tricks.[3]

Speed and effectiveness in training operators are another challenge in agile manufacturing, particularly for novice operators and when standard operating procedures are changed. Currently, factories rely heavily on word of mouth because paper and digital material are difficult to organize and often outdated.

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FIGURE 1. An operator interacting with the cognitive assistant by voice and graphical user interface.

This results in high variations in operating quality, efficiency, and effectiveness. To mitigate these shortcomings, we introduce a mobile-based cognitive assistant that enables the transfer of expert knowledge to novice operators. Our cognitive assistant supports voice and text interaction and is accessed by a mobile device that operators can carry around the production line (Figure 1). Infrastructure stereoscopic cameras enable context-aware features (e.g., operator tracking) to optimize the interaction with the cognitive assistant in a privacy-aware fashion.

We developed our solution in collaboration with multiple agile manufacturing partners, namely two detergent factories in The Netherlands and in Italy, a fabric factory, and a fabric worker training school in Italy. The workers in detergent factories operate a production line comprised of numerous types of machines, from robot arms that stack boxes on a pallet to filling machines that inject detergent into canisters. The fabric workers operate loom machines comprised of two main parts, the weft and warp side. The production activities in these factories are notorious for imposing a high cognitive workload on their operators. An ever-changing selection must be produced that requires unique machine configurations, troubleshooting, and optimization techniques.

In the context of detergent production, even the characteristics of the components of a product can change abruptly (e.g., viscosity), requiring new machine settings and/or techniques. Operators work in shifts, they are remarkably busy, and existing knowledge-sharing methods (e.g., drafting a short report after an 8-hour shift) are time-consuming and error-prone. Therefore, the ability to share new knowledge rapidly and accurately is essential in such challenging manufacturing contexts.

COGNITIVE ASSISTANTS FOR KNOWLEDGE SHARING

Since 1965, efforts have been made to acquire knowledge and store it in a knowledge base (KB), such that it could be used by AI systems to support human workers. Expert systems, or one of their modern counterparts, cognitive assistants, support humans in knowledge-intensive tasks, such as operating an agile manufacturing line. These AI systems are referred to as knowledge-based systems since they rely on a KB to support their users. Traditionally, the KBs, on which these AI systems rely, are static; they are defined by developers in collaboration with domain experts or scraped from existing databases. This is not surprising as the process of manually acquiring knowledge is resource intensive, a phenomenon known as the knowledge-acquisition bottleneck.[4] Using a static KB has various shortcomings: 1) knowledge changes over time; 2) the process of creating an exhaustive KB is resource-intensive; 3) it is difficult to update when gaps in the KB are identified; and 4) the KB misses important contextual information.

Recently, researchers have made considerable progress toward efficiently building and maintaining KBs for AI systems. For example, active learning from datasets,[5] crowdsourcing the process,[6] extracting knowledge from online forums,[7] and interactively learning from (expert) users. All aforementioned solutions are promising, and all four could be integrated in a single system. However, knowledge is more than 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] Although some contextual information can be collected autonomously, such as the location of the user (Figure 2), understanding user's experience (UX), insights, and values is difficult without interacting with the user, for example, via a chatbot.[9] Recent research has shown that factory workers provide much richer information, including explanations of their actions, when conversing with a voice assistant compared to sharing their knowledge on paper.[10]

Recent research on tacit knowledge in manufacturing has shown the immense value tacit knowledge can bring.[11] We now know that tacit and explicit knowledge exist on a continuum and that tacit knowledge can be converted into explicit knowledge.[12] Although our understanding of tacit knowledge has grown, it remains resource-intensive to effectively collect and share. In the manufacturing industry, researchers have manually extracted tacit knowledge using human motion capture, videos, and field interviews with experts and

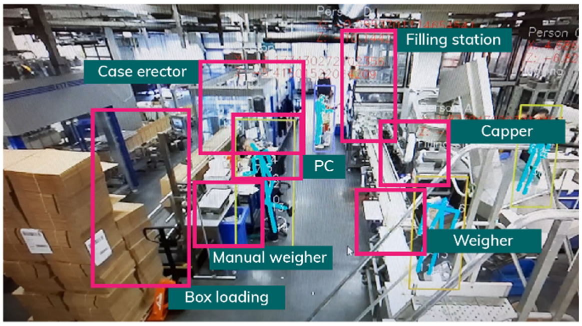

FIGURE 2. Stereoscopic camera view to track the operator's location and activity. Operators are tracked as 18-point skeleton frames thus protecting their privacy.

beginners.[13] However, this process requires skilled analysts to perform. Data analysis techniques can be used to identify tacit knowledge and store it in databases.[14,15] Granted, these techniques do not provide operators with the opportunity to describe how or why they are doing things, nor do they offer a way to share their knowledge. To solve some of these challenges, a (n) (embodied) cognitive assistant could facilitate the sharing of tacit knowledge in a factory through dialectic interactions.[16] To the best of our knowledge, no existing AI system has demonstrated the ability to collect and share tacit knowledge in agile manufacturing settings.

SYSTEM ARCHITECTURE

The cognitive assistant provides human-centered support to the operators on the production line; it "understands" how to collaborate effectively due to its context awareness, its knowledge graph, user profile, and ability to continually learn Figure 3. Context awareness is provided by a data stream from machines and cameras (to track the operator's location and activity).

The live data streams from the machines provide the cognitive assistant with information on the machine settings and status. These data are mapped to a knowledge layer that enables the cognitive assistant to identify relevant knowledge for users. Furthermore, by tracking context and production performance, it can predict when operators are using novel knowledge to reach higher performance (i.e., the best practices). In turn, the cognitive assistant can initiate an exploratory dialog with the operator to acquire (tacit) knowledge about these best practices. Any knowledge that is acquired is stored in the knowledge graph with relation to the context of its use. A knowledge graph represents a network of real-world entities (e.g., machine components, events, products) and

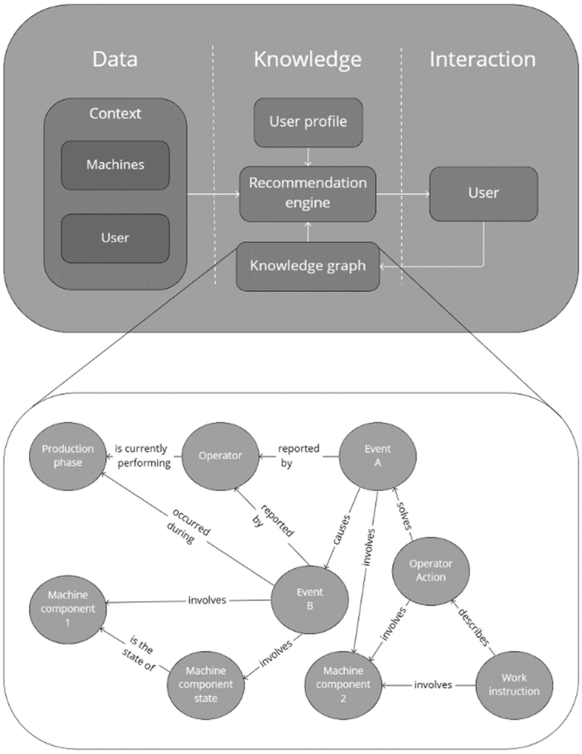

FIGURE 3. Cognitive assistant architecture, interactions, and a magnified view of its knowledge graph.

their relationships (e.g., causes, is part of). This enables the cognitive assistant to recommend and explain the acquired knowledge if a comparable situation recurs. For example, if an operator would ask for help with a foaming product, the cognitive assistant might respond with the following information: "*I found the following causes for the described problem: high pressure, blocked nozzle, and low product viscosity. I suggest the following solutions: reduce pressure and clean the nozzle filter*."

The cognitive assistant uses the following inputs for its recommendations: operator position, operator activity, knowledge graph, live machine data streams (e.g., machine settings and status). In turn, the cognitive assistant delivers the following output(s): task descriptions (e.g., work instruction steps), advice (e.g., suggesting potential causes or solutions to a problem), best practices (e.g., best settings for a product), media (e.g., video training material), and knowledge requests (e.g., why did the operator change the settings).

Knowledge Representation

Knowledge representation (KR) methods organize relevant information in a specific domain in a structured way, allowing its use by intelligent systems, and reasoning programs.[17] Web-based services, software applications, robots, and human users make use of the represented knowledge through queries, to perform a task or provide a service. There are multiple types of knowledge representation methods. These methods can be categorized according to the type of knowledge they illustrate, namely *declarative*, *procedural*, *situational*, or *strategic*.[18] These categories can be mapped onto the explicit-to-inexpressible tacit knowledge spectrum. While explicit knowledge is already documented and easily expressible, inexpressible tacit knowledge acquisition requires the implementation of specialized knowledge-acquisition methods.

Declarative knowledge describes concepts and their semantic relationships. Machine component descriptions, issue description, root cause, and problem solution are examples of this type of knowledge in the manufacturing context. A lot of declarative knowledge can be extracted from existing factory documentation.

Procedural knowledge describes the procedures and methods to complete an action. Know-how on machine configuration and problem-solving procedures fits into this category of knowledge. Procedural knowledge contains expressible tacit knowledge, such as a description of steps, and inexpressible tacit knowledge, such as the "craft" operators develop through experience. Some explicit procedural knowledge may already be documented by factories and can be used by the cognitive assistant. The cognitive assistant can update existing procedural knowledge through dialog with operators (e.g., by asking "*what did you do?*") and by observing their actions (e.g., operator tracking).

Situational knowledge is higher level knowledge. It determines when and where to use the knowledge available in the specific domain of application. An example of this knowledge is the selection of methods, a solution, or a specific formula for problem solving. The ability of an operator to know when to use knowledge also contains expressible and inexpressible tacit knowledge. The cognitive assistant can acquire this knowledge through dialogs, data analysis, graph analysis, and other AI techniques.

Strategic knowledge describes the reasons why a method or solution is selected. This last category may involve intuition and generalization, i.e., knowledge that is challenging for humans to explain and challenging for AI to acquire. In the manufacturing context, an operator uses strategic knowledge to adapt the solution for one problem to another similar problem. Strategic knowledge is strongly related to inexpressible tacit knowledge, therefore, the most challenging to acquire. The cognitive assistant can obtain this knowledge through exploratory dialogs (e.g., by asking why an operator did something), data analysis, graph analysis, and other AI techniques.

Our solution implements a knowledge graph (a declarative knowledge method) as an integrator element to connect procedural and situational knowledge methods in a coherent way. The knowledge graph describes and relates the main concepts associated with the manufacturing line through nodes and links, including production phase, machine components, product components, machine and product states, events, causes, and operator actions, among others (Figure 3). This representation allows connecting machine components with events, and actions to solve problems, enabling the cognitive assistant to navigate through the knowledge graph to get the most suitable recommendation for the operator. The "operator actions" nodes allow the user to process descriptions and the best practices describing the know-how of the operators. Action-type nodes provide procedural knowledge, while their relationships with events, and machine components derive situational knowledge needed to determine when to implement such a solution.

THESE METHODS CAN BE CATEGORIZED ACCORDING TO THE TYPE OF KNOWLEDGE THEY ILLUSTRATE, NAMELY DECLARATIVE, PROCEDURAL, SITUATIONAL, OR STRATEGIC.

We use Neo4j,[a] one of the leading graph database platforms, to host the KB that powers our cognitive assistant. Neo4j also allows for performing graph analytics, through the Neo4j Graph Data Science (GDS) library. GDS is a set of preloaded graph algorithms that contribute to the description of complex structures to unveil hidden patterns. Some of the analyses that can be performed through GDS are centrality, community detection, similarity, path-finding, prediction of topological links, and node embeddings. Centrality algorithms are used to determine the importance of different nodes in a graph. This algorithm can be implemented to identify the machine/product components that are prone to present more events (potential faults), the most popular solutions in the network, and the root causes that lead to more events, among others.

Pathfinding algorithms aim to find the shortest path between two or more nodes. This algorithm has

[a]https://neo4j.com/

great potential to determine the shortest procedure to solve an event and the shortest explanation of a cascading event. Community detection determines how groups of nodes are clustered and their tendency to break apart. This algorithm enables the cognitive assistant to identify interrelated events whose relationship has not yet been determined, as well as to gauge rare states and events (i.e., entities that are not connected to the rest of the network) that are depicted as "islands" on the knowledge graph.

Similarity algorithms are widely used in recommendation systems to assess the similarity between a pair of nodes. This analysis is used in the cognitive assistant context to extrapolate solutions and recommendations from one node to its pair, in cases in which the latter lacks information. The cognitive assistant can use the machine data streams to determine the overall performance production. A new best practice can be identified by comparing current performance with historical data. In turn, the cognitive assistant can collect any available data on best practice using context awareness and conduct a short interview with the operator to acquire relevant expressible tacit knowledge. In addition, it can use data analysis techniques to reveal inexpressible tacit knowledge.

HUMAN-ASSISTANT INTERACTION

The cognitive assistant's main user interface is a mobile app that supports interaction by voice, text (Figure 4), touch, graphically, and camera. This provides high adaptability; the voice interface can be used with a headset for hands-free and gaze-free interaction, and the user can take out the mobile device to look at an image or video when necessary.

The duration of the interactions is minimized, as the cognitive assistant can use its contextual awareness (operator location, activity, and machine data streams) to acquire important information and accelerate user interaction. This also facilitates intelligent conversation breakdown recovery. For example, if it is not clear which specific component the user is referring to, the cognitive assistant can infer the correct one based on the context (e.g., the operator's location).

Lean Information Exchange

The cognitive assistant suggests responses for the user based on the context and previous conversation steps. For example, when an operator starts to describe an issue, it suggests additional symptoms for the operator to check. In addition, it can use the operator's location to prefill information about the location(s) of an issue. This feature aims to make dialogs more

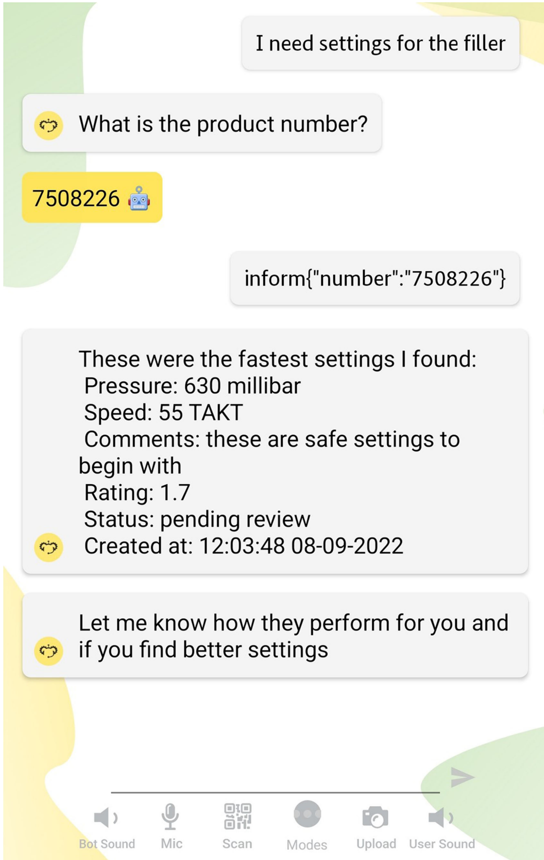

FIGURE 4. User requests filling settings for a product.

efficient by narrowing down possible conversation steps and encouraging the use of standardized vocabulary. Dialogs for training operators toward standardized terminology not only enables usage of synonyms of technical terms, but it also harmonizes vocabularies used by various stakeholders across the factory. The long-term goal is to train operators to provide high-quality data for further analysis, and to evaluate the progress of on-the-job training.

Lean Timing for Engaging Operators

Anonymous position and activity tracking enables the cognitive assistant to engage operators in issue reporting at a suitable time. Operator tracking (e.g., activity recognition) enables the cognitive assistant to detect opportune moments to report various types of issues and facilitate user interaction. The goal of this feature is to reduce the cognitive workload for operators by attempting to achieve balance between prompting the operator to recall necessary information and providing step-by-step documentation of issues in small snippets, parallel to performing issue handling actions. Additionally, it aims to reduce overreliance on operators' organic memory to report an issue by supporting operators with dialogs that enable on-the-spot documentation, parallel to issue handling, and production-line configuration activities.

Transparent Processing of User Suggestions

A context analysis we performed at the factories revealed that operators were unhappy about how their suggestions for improvements were handled as they did not receive any progress updates. The cognitive assistant provides the needed transparency by creating GitLab[b] support tickets for the operators. Consequently, operators can track the status of suggestions. This provides a central, transparent platform for operators to collectively track and discuss improvements to the knowledge base, the cognitive assistant, and the production line.

USAGE SCENARIOS

Active Downtime

Operators are exceptionally busy keeping the production line running smoothly and handling issues. However, there are moments during a shift when the line is stopped and they must wait for other departments to perform tasks they depend on (e.g., technical support, quality control, or logistics). During this period, the cognitive assistant can alert operators to recent updates and to standard operating procedures, recommend time-consuming training material, or provide an update on the knowledge they have provided (e.g., if it has been approved and how frequently it has been used). The cognitive assistant can keep track of what training the operator has already received to avoid repeated suggestions or identify when a refresher may be necessary.

Machine Reconfiguration

As operators reconfigure the production line, the cognitive assistant can provide recommendations relevant to the current step, for example, if the operator is standing next to the detergent filling machine during the clean phase, it can recommend the best practice for cleaning procedures or provide warnings regarding recent problems other operators have been facing. It can also answer simple questions the (novice) operators have about a task. If (novice) operators do not know how to request specific knowledge (e.g., they do not know the correct jargon), the cognitive assistant can aid them purely based on the context. The cognitive assistant will use the operator's position, activity, and machine status to provide a relevant recommendation.

[b]https://about.gitlab.com

Issue Handling

During issue handling, the cognitive assistant can provide suggestions for investigating actions, potential causes, and solutions to the issue. It can also collaborate with the operator to identify the root cause of a problem by using the 5-Whys approach, a proven agile manufacturing technique.[19] Even if the issue does not exactly match one in its knowledge base, it can use similarity models to find knowledge about similar situations that may be applicable. To prevent issues from occurring, the cognitive assistant can use machine learning models and acquired operator knowledge to alert operators in advance. Furthermore, the cognitive assistant can support the operators in efficient documentation of the issue and use the opportunity to acquire their knowledge.

Suggestions for Improvements

Operators can suggest improvements to the knowledge base, the interaction with the cognitive assistant, and the production line when it suits them. In addition, the cognitive assistant uses (machine learning) models to identify deviations from the best practices and applications of tacit knowledge. This enables the cognitive assistant to proactively acquire new best practices and, if necessary, interview the operators to capture their insights and thought processes.

DISCUSSION

User Interaction

Interacting with the cognitive assistant by voice or text can be cumbersome and, to a certain extent detrimental to actual operator performance. Input modality is paramount not only for operator's performance, but also for UX levels. In turn, satisfactory UX levels will be key to promoting the adoption of the cognitive assistant. Thus, the device that hosts the cognitive assistant becomes its embodiment and defines the interaction between the operator and the cognitive assistant. On the one hand, voice input is known to be error prone, and its performance will only deteriorate in noisy environments such as on a production line. On the other hand, typing text to interact with the cognitive assistant may not always be practical due to operator's equipment (e.g., gloves), or an activity that requires both hands to perform (e.g., adjusting the carousel torque while under the filler). In the detergent manufacturing environment, noise levels can reach 80 db(A) and operators are pressed for time. Therefore, we trained the cognitive assistant to understand keywords for several common features and suggest user responses as buttons to minimize interaction time and misunderstandings.

Knowledge Management

Factory management is interested in using cognitive assistants to identify best practices, share them, and ensure that all operators follow them. However, expert operators are proud of their unique ways of operating and may resist standardization. Sometimes, during conversation, the experts omit important information, either, because they find it too obvious, are not aware of the importance of the omitted information, or intentionally, to keep competitive advantage, status, or power.[20] Typically, the management wishes to maintain control over what the best practice is, i.e., approve any new knowledge acquisitions. However, this might inhibit the speed of knowledge sharing. Peer assessment of new best practices using operator ratings could benchmark and accelerate the speed of knowledge sharing among operators. Peer assessment could also be used to maintain the accuracy of the knowledge base over time, as best practices will inevitably change. Another challenge is how to handle the cold start problem, namely, that the cognitive assistant needs to learn from operators before it can provide assistance. Understandably, users may reject the cognitive assistant if it was introduced as a blank slate. Therefore, we initiated the cognitive assistant with knowledge we manually acquired by interviewing operators and processing existing documentation.

Operator Safety

Activities performed on the production line, near or with heavy machinery, entail the inherent risk of serious injury or even death. Spontaneous interaction with the cognitive assistant could distract the operator and cause physical harm. We believe the context-aware component of the cognitive assistant can minimize the risk of operator injury. The cognitive assistant not only tracks the physical location of the operator on the production line, but also recognizes their activity (e.g., operating a hydraulic press). In the case of operating heavy equipment, the cognitive assistant should suppress its proactive prompting to prioritize operator's safety over the potential to capture a new best practice. Here, detecting opportune moments to interact with the operator is not just a sought-after functionality, but an essential safety feature.

Ethical Considerations

An AI-powered system such as the cognitive assistant naturally raises a multitude of ethical concerns. For example, the long-term effects of an AI cognitive assistant on the operators, who use it daily for on-the-job training, have not been explored before. Here, we intend to help operators learn by forming a synergistic relationship between the operator and the cognitive assistant. However, we may be providing the "path of least resistance" to operators where they uncritically follow and over-rely on the instructions of the cognitive assistant. Learning-assessment tasks periodically delivered via the cognitive assistant (e.g., multiple choice questions) could help evaluate the actual expertise levels of the operators. The rich data streams necessary to the cognitive assistant can be misused by the management to intrude operators' privacy and violate their worker rights (e.g., excessive tracking). Data management plans, policies, and methods that protect and respect users' privacy and rights, respectively, are foundational in the dawning of Industry 5.0. Finally, it is not easily understood who owns the knowledge that experienced operators generate with the cognitive assistant. One could claim that the tacit knowledge captured from the operators, and formalized with the cognitive assistant, does not differ much from intellectual property generated via other avenues in corporate settings (e.g., submitting a patent).

CONCLUSION

We presented an AI-powered cognitive assistant that provides cognitive support to agile manufacturing operators by orchestrating the sharing of (tacit) knowledge from experts to novices. Cognitive aid is provided in the form of dialectic recommendations for standard work instructions, decision-making, training material, and knowledge acquisition. Our next step is to deploy and evaluate our cognitive assistant in the industrial agile manufacturing settings of our partners. We aim to steer the cognitive assistant in alignment with sound principles of user experience, knowledge management, operator safety, and AI ethics. Future research directions include exploring user interaction modality and style on the user experience, safety considerations, and long-term effects on the operator's performance, cognitive workload, knowledge retention, and well being.

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