Bridging the Gap between Knowledge and Human Expertise: Integrating Explicit and Tacit Knowledge in Maintenance Operations*

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Abstract

Knowledge transfer is crucial in establishing an institutional memory that guarantees informed decisions, continuity, and improved productivity and efficiency. It enables sharing best practices and insights among individual workers and teams, and creates collective and sustainable capabilities. However, effective knowledge transfer leads to several challenges in capturing and sharing the knowledge of more experienced workers, primarily what is known as tacit knowledge, due to inadequate technological support and cultural and organizational barriers. This paper proposes overcoming these obstacles with a technological solution based on the Knowledge-Assisted Visual Analytics model to collect and share explicit and tacit knowledge while interacting with a visual information system. We tested the validity of our approach in a real use case designed in collaboration with the Spanish Army and affecting two different maintenance parks. The Visual Analytics tool creates a unique knowledge base that centralizes all the knowledge about maintenance operations and includes both the explicit knowledge included in a set of official, though incomplete, handbooks and the tacit knowledge operators have developed over time. This tacit knowledge is captured in two ways due to the differences in the parks, the material, and the personnel involved. In one case, it is externalized using videos, whilst in the other, we relied upon a focus group where experts usually discuss unclear parts of the handbooks or tricks to be more efficient.

Keywords

Tacit Knowledge, Explicit Knowledge, Visual Analytics, Knowledge Transfer

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1. Introduction

In most organizations, there is a demanding need for high-level expertise to diagnose and resolve complex issues across diverse operations [1, 2]. Knowledge transfer is necessary to building an institutional memory that helps organizations make informed decisions based on previous experiences, ensure process continuity, and improve productivity and efficiency by applying the tacit knowledge developed by workers [3]. In particular, the efficiency and effectiveness of maintenance operations depend on the knowledge and expertise of the involved personnel. However, part of the required expertise resides in each individual as practical skills, know-how, and intuitions that are difficult to express or formalize [1]. Such tacit knowledge is fundamental in maintenance due to the diverse and often non-routine nature of tasks, the involvement of multiple disciplines, and the constant evolution of technology. Experienced workers develop mental models that enable them to identify and address problems effectively, but those often remain siloed into experts instead of feeding a shared institutional memory [1]. Transferring

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and reusing this tacit knowledge within an organization is particularly complex as it depends on how it can be elicited and deployed, taking into account that, in many cases, this kind of knowledge cannot be formalized [4]. The difficulty of effectively externalizing and leveraging tacit knowledge in maintenance operations leads to several critical issues, mainly related to employee turnover or retirement. Organizations face the risk of knowledge loss when more experienced workers leave, and there is no institutional memory [3]. This loss contributes to higher maintenance costs, delays, and compromised safety due to slower problem-solving, decision-making, and increased process errors [5].

Despite the critical role of tacit knowledge in maintenance, formalized approaches for its capture and transfer remain underdeveloped in many organizations [5]. Traditional information systems and document repositories often fail to capture the individual know-how and skills of the employees. The case of explicit knowledge is different, understood as all the data physically stored in the system, such as official manuals, handbooks, and procedures [6]. Integrating tacit and explicit knowledge helps to develop a more precise understanding of the maintenance procedures. For this reason, there is a growing recognition of the need for strategies and mechanisms to effectively externalize tacit knowledge, transforming it into a more accessible and usable source [2].

One of the strategies to externalize tacit and explicit knowledge is to use visual analytics (VA) interfaces that enable the exploration and analysis of complex data through visual representations and analytical reasoning. While interacting with the visual elements in the interface, the users analyze and reason over the data more efficiently [7]. Users' tacit knowledge significantly influences this process, especially in contexts such as maintenance operations. Several cognitive models explain how knowledge flows in a VA system [8, 9, 10]. However, there is still a need to research knowledge externalization and transfer, especially considering that the domain experts could have no technical background and might not be particularly motivated to share their skills, which can make the design of such tools more challenging.

This paper addresses the challenge of externalizing and sharing tacit knowledge about maintenance operations in a military setting. In collaboration with the Spanish Army, we were engaged in creating institutional memory to support the creation of a unique maintenance center that will put together procedures currently distributed geographically in different parks and performed by a hybrid cohort of workers. Two key requirements were considered when deciding how to design the VA tool: confidentiality and trust. Explicit and tacit knowledge contain highly sensitive data that should be protected. At the same time, the information provided has to be based on real experience, so the source has to be reliable and traceable. For this reason, we opted for a human-centered approach where Artificial Intelligence (AI) techniques support humans in creating such a collective institutional memory. Hence, the VA tool does not use models based on external data training nor apply non-explainable algorithms, which is unacceptable to our stakeholders. The VA tool makes it possible to interact with explicit knowledge, made up of handbooks, and tacit knowledge, which is captured using videos and explanations gathered from actual experts.

In the next section, we introduce the cognitive models proposed in the literature to formalize the knowledge flow in VA. Section 3 introduces the knowledge base used, and Section 4 describes the use case designed. Finally, Section 5 draws some future work, and some conclusions and implications of the work.

2. Explicit and Tacit Knowledge in Visual Analytics

VA tools offer interactive visualizations to support the analytical and reasoning processes [11]. The analytical reasoning is not fully automatable and heavily relies on users' initiative and domain experience. At the same time, the visual interface supports the perception of patterns and connections hidden in data [12]. The ultimate goal of combining analytical reasoning with the design of interactive visualizations is to create an environment where the users can gain insights and discover new knowledge from the data [10]. Understanding how knowledge is shared and leveraged within the whole VA process is key to efficiently supporting human capabilities and the analytical methods [12].

Effective knowledge sharing ensures the dissemination of critical insights among employees horizontally and vertically, leading to improved innovation, performance, and efficiency [13]. It recognizes the distinction between *explicit knowledge*, represented as resources that can be physically stored and analyzed, like manuals, tutorials, and diagrams, and implicit or *tacit knowledge*, which is personal, experience-based, and challenging to articulate [12]. VA tools can be a helpful support to combine different sources of knowledge, externalize the tacit knowledge, and integrate it with explicit knowledge through analytical methods and visualizations [7].

In this work, our interest focuses on tacit knowledge and how it can be externalized and shared through a VA tool. Tacit knowledge significantly contributes to performance in domains where practical experience is indispensable, such as healthcare, manufacturing, and maintenance operations. It represents the "know-how" individuals draw upon in action but is difficult to access or express in language [14]. The operators rely on their abilities and experience to carry out specialized tasks. The operators' experience-based insights should be captured and analysed to prevent losing important information and effectively transfer the entire procedure to other operators or even automatic systems. This process is called *knowledge externalization* [9].

Wang et al. have proposed a knowledge-assisted visualization system to manage information about bridge assets and support decision-making for the US Department of Transportation [9]. The system is based on an ontological structure built by collecting information directly from bridge managers and other domain experts. It also offers an interface to allow users to interact with bridge data through textual, geospatial, temporal, and relational visualizations. Each one of the system components has been designed to respond to one of four different knowledge conversion processes: *internalization* to discover new insights, *externalization* to enrich the ontology with new concepts and relations, *collaboration* to share knowledge with others in charge of the same operations, and *combination* to extract information to external sources and integrate it to the ontology. In the externalization process, the user extends the ontology with new knowledge from her own experience or the new insights gained while interacting with the visualizations in the system.

The four knowledge conversion processes are formally defined by mathematical equations and a cognitive model to determine how the explicit and tacit knowledge flows through four entities and three processes. The entities include the data D from where the explicit knowledge K^E is extracted, the tacit knowledge K^T coming from the user experience, the knowledge base KB to integrate K^E taking into account a specification S that includes all the settings defined by the user's interaction with the system. The processes defined between entities are the visualization V to represent knowledge and data as an image, the perception P, and the exploration E of the user while interacting with the visualization. The proposed model is based on the *Simple Visualization Model* by Van Wijk [8], where there is no distinction between explicit and tacit knowledge.

Based on the formalism introduced by the models of Wang et al. [9] and Van Wijk [8], Federico et al. have proposed the Knowledge-Assisted VA model for representing the knowledge flow in VA systems [10]. Concerning the others, they have formalized the analytical reasoning as a set of methods A in charge of analyzing the data automatically and extracting the explicit knowledge based on the specifications configured by the user exploring the system. They have also introduced two different processes to externalize the tacit knowledge. One of them is a direct externalization X to formulate the tacit knowledge as the explicit directly. The other one consists of inferring the tacit knowledge by applying interaction mining techniques to the users exploring the interface.

The Knowledge-Assisted VA model completely represents the four knowledge conversion processes. It overviews how information and experience flow between machines and humans through a VA tool. When applying this model to build a solution, there is no clear definition of how direct externalization works and how the tacit and explicit knowledge can be integrated and visualized in a unique interface. For this reason, in this paper, we introduce an additional element to this model, changing the direct externalization process X for a knowledge base, as described in the next section.

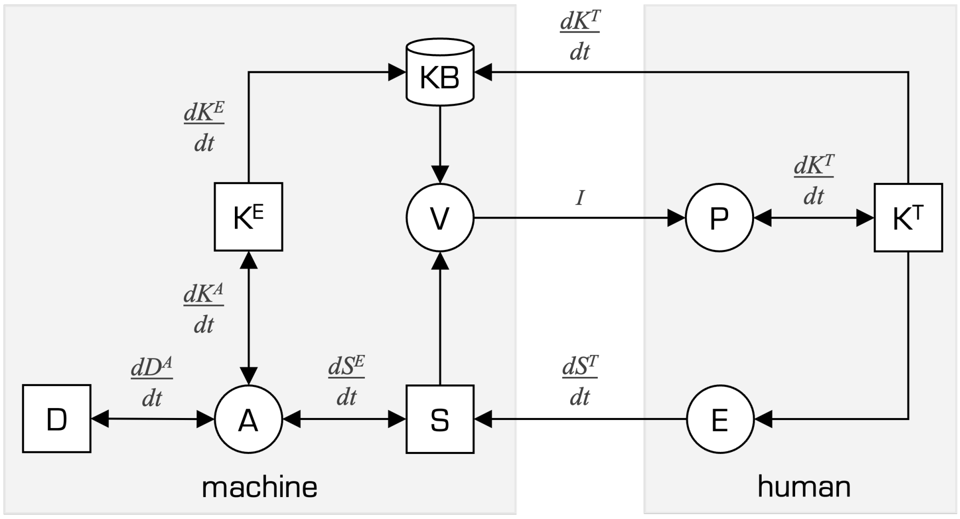

Figure 1: A modified version of the Knowledge-Assisted VA model by Federico et al. [10], with the knowledge base *KB*, four entities (the data *D*, the explicit knowledge K^E, the tacit knowledge K^T, and the specification *S*), and four processes (the automatic analysis *A*, the visualization *V*, the perception *P*, and the exploration *E*)
.

3. A Knowledge Base for the Knowledge-Assisted Visual Analytics Model

Several models formalize the role of explicit and tacit knowledge in the VA workflow. In this paper, we are particularly interested in understanding how to elicit tacit knowledge from domain experts to integrate it into a VA tool. To this scope, we propose introducing a knowledge base into the Knowledge-Assisted VA model by Federico et al. [10] as an ontological structure to collect and interact with explicit and tacit knowledge. The knowledge base will be the connection between the visualization and the knowledge flowing from the machine to the human and vice versa. Its introduction has been inspired by the contribution of Wang et a. [9], where the knowledge base was limited to structure the explicit knowledge extracted from the data stored in the system.

In this work, the knowledge base will be in charge of integrating the tacit and explicit knowledge. The conceptual model in Figure 1 represents how the knowledge flows between two leading actors, the machine and the human, and defines a set of containers and processes. The containers are the input and output of the model, including the data D stored in the system, the explicit knowledge K^E extracted from the data, the specification S used to make decisions about the analysis and visualization methods to apply, and the tacit knowledge K^T coming from the user's experience. The processes are defined through mathematical formulas to transform the input into the output within the model, like the automatic methods A to analyze the data and generate the explicit knowledge, the perception P and the exploration E of the users, and the visualization V.

The knowledge base KB is included in the conceptual model to map analyzed data, insights, and information from both the system (i.e., the machine side) and the user (i.e., the human side) into an ontological structure. On the machine side, available data is analyzed to extract valuable information based on a given specification S and generate knowledge K^E stored in the knowledge base as a set of concepts and relations between them. All the knowledge collected in KB is visualized through the process V and, also in this case, based on the given specification S.

On the human side, the tacit knowledge K^T comes from each individual's experience, but the interaction with the system also influences how the user perceives the image I of the knowledge base generated by the visualization process V, and how the user explore E the visualization V through the specifications S. While interacting with the visual interface, the user learns about the application domain and improves her experience. The externalization of this knowledge requires finding a way to collect from the user what she knows about the domain before and after interacting with the visual application.

Time is a fundamental component of the model. The information shared within the system evolves over the time the interaction between the user and the visualization lasts. As shown in Figure 1, the input and output are transformed through differential formulas to describe how the quantity of a specific container varies over time. In particular, the knowledge base receives explicit and tacit knowledge as input, giving a visual representation as output. It continuously evolves, changing the information included depending on the given specification *S*. The ontology allows the definition of a flexible structure where it is possible to create new concepts, establish new relations, and modify existing ones. Consequently, the application will also adapt the visual representation to the changes included in the knowledge base. Users will also perceive these changes, enriching their insights into the domain and influencing the externalization process.

4. A Use Case: The Military Maintenance Operations

Maintenance operations refer to a set of technical or administrative activities fundamental for ensuring the proper functioning of the facilities in an organization. In sectors like manufacturing and industry, these operations often rely heavily on the tacit knowledge of employees [15], like technicians and practitioners. While the official handbooks provide explicit guidance about the main procedures, they fail to capture the personal experience of the operators, especially for diagnosis problems, anticipating errors, or adapting repair strategies to the current context. Externalizing this knowledge is a complex process, but it is especially important in situations where transferring this embedded know-how is needed, as experienced workers retire or change roles in the organization, which is the case in the Spanish Army. Lately, many industries have been trying to establish strategies to support knowledge transfer among their employees. Cutting-edge technologies, like expert systems, digital twins, augmented reality, and visual analytics platforms, are being used for this purpose [16].

In this paper, we have designed a use case in collaboration with the Spanish Army to propose a solution to a lack of such institutional memory that they will be experiencing as they are creating a unique physical center to centralize the maintenance operations currently distributed geographically in different parks. Each park has a hybrid set of military and civil workers with different responsibilities, some of which cannot be forced to move to the new location. Hence, one of the main challenges is guaranteeing that the knowledge of experienced workers is not lost. To better frame the problem and its multiple nuances, we had several meetings with officers of various ranks, and we visited two maintenance parks with entirely different features, from the material involved to, what is more important, the composition of the maintenance team. In one of the parks, which involved heterogeneous mechanical and electronic activities, there was a high number of civil workers, whilst in the other park, the workforce was mainly composed of military personnel. Our proposal is a VA tool that supports knowledge transfer of maintenance operations between workers with different experiences and integrates tacit knowledge captured using different methods, depending on the protocols and procedures of the working environment and the preferences and availability of the involved workers.

Based on the conceptual model in Figure 1, we have defined a workflow diagram to describe how the proposed tool works (see Figure 2). One of the main issues we have to deal with is the confidentiality of the knowledge collected from different sources, including handbooks, focus groups, and expert videos. This is reflected in the design choices we made to define the three main steps of the workflow: *processing*, *parsing*, and *externalizing*. All this knowledge is stored, processed, and structured locally, and we use the Stanford CoreNLP [17], a Natural Language Processing (NLP) toolkit, to analyze the textual content and avoid models based on massive and external data training. For the same reason, we have built a knowledge base from scratch to guarantee full access and control over the content and guarantee trustworthiness. The following subsections give an overview of each step. Some details of the images and descriptions are not included due to a Non-Disclosure Agreement (NDA) signed with the Spanish Army.

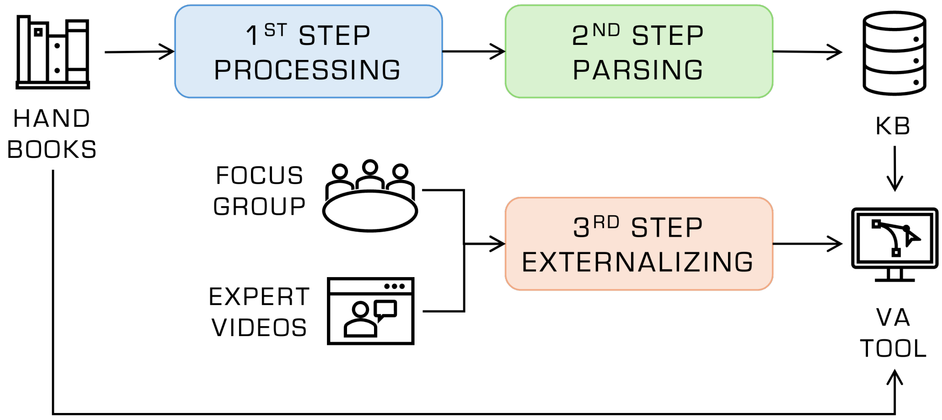

Figure 2: Workflow diagram of the VA tool with three main steps: *processing*, *parsing*, and *externalizing*.

4.1. 1st step: Processing

The first step of the workflow (see Figure 2) consists of a data processing pipeline that extracts raw text from a set of handbooks in PDF format. The handbooks are the official sources of information used in the maintenance parks, and describe the procedures to be carried out. They represent the explicit knowledge needed to develop the proposed tool. Text is extracted from each PDF document and cleaned of irrelevant content, building a structured dataset as input for the second step. The cleaning includes operations like conversion to lowercase, removal of special characters and symbols, and adjustment of line breaks and list items to prepare the document structure.

4.2. 2nd step: Parsing

The second step of the workflow (see Figure 2) aims at extracting the explicit knowledge to include in the knowledge base in the form of concepts and relations. The knowledge base makes it easier to integrate heterogeneous data, structured and unstructured, in different formats and coming from various sources. Moreover, the proposed VA tool focuses on the semantics of the domain. To this scope, it is crucial to apply AI techniques, particularly the CoreNLP Toolkit [17], to identify the most relevant concepts and relations. The raw text processed in the first step undergoes a hierarchical parsing to identify different levels of maintenance operations. The description of the operations in the handbooks follows a specific pattern to organize the information, as well as a list of sub-processes and individual actions to disassemble and assemble components. This second step splits the text into sentences and recognizes which sentences correspond to these patterns using regex-based pattern matching. The result is a sequence of sentences containing different elements of the operations' description.

The knowledge base is then built by analyzing the operations' description elements to extract the most representative concepts and relations. To this scope, we have performed a semantic analysis applying techniques from the CoreNLP Toolkit [17]. The analysis pipeline includes tokenizing the text into individual words and punctuations, tagging each word in a sentence with its part-of-speech (i.e., grammatical role), creating a syntactic tree structure based on the dependencies between the words in a sentence, and normalizing the words with their base forms. We also define a hierarchical categorization of the concepts, where operations act as parent nodes, while sub-processes and individual actions are child nodes. Metadata is embedded within each node, including a detailed description of the operations, sub-processes, and actions.

4.3. 3rd step: Externalizing

The third step (see Figure 2) is in charge of externalizing the tacit knowledge. We carried out two procedures due to the specific features of each of the involved parks. In one of them, the maintenance operations are mainly performed by highly specialised military personnel. Their participation in the project was driven by an urgent need to transfer knowledge to new generations. The most suitable way to capture the officers' knowledge was by recording them performing tasks. These videos are a valuable and trustworthy source of information from each expert. The videos are recorded from three different points of view: first-person camera, third-person fixed camera, and third-person tracking camera. The first-person camera, also known as a point-of-view or POV shot, shows the scene from the subject's eyes, and it is recorded while asking the expert to wear the Meta Quest 3 headset. The third-person fixed camera refers to filming the scene, positioning the camera on a tripod in a fixed position from which it is possible to observe the subject and her actions. In the third-person tracking camera, the camera follows the subject and all her movements. Filming from the three perspectives allows for capturing all the details of the operation. We also applied the think-aloud technique, asking experts to describe what they were doing and why. We analyzed the transcription of the videos to identify the operations and actions performed.

However, this approach was not valid in the other maintenance park, where most operators were civil personnel who were less engaged in the project. They couldn't be recorded, but they found participating in an online focus group a less invasive option since they had already participated in similar practitioners' forums. The focus group lasted two weeks, during which 25 workers with various responsibilities were invited (11 accepted) to answer questions about six topics related to their expertise. For each topic, participants were shown the corresponding chapters in the handbooks and were asked to comment on missing, unclear, or difficult-to-learn topics and tricks they used. At the end of the focus group, we collected 21 messages.

The externalization of tacit knowledge is achieved by bridging the gap with explicit knowledge and creating an association between expert videos, annotations, and the handbooks' concepts. This association is made possible by the conceptualization included in the knowledge base. As shown in the next section, all the resources stored in the system (i.e., handbooks, expert videos, focus groups) are automatically analyzed to identify the knowledge base concepts that relate to them. The knowledge base establishes then how the information, insights, and experiences flow toward the visual interface: from the explicit K^E and the tacit knowledgeK^T to the knowledge base KB and from the knowledge base KB to the visualization V (see the conceptual model in Figure 1).

4.4. Visual Analytics Tool

In this work, we propose the design of a VA tool for transferring knowledge from more experienced workers to novice employees to support the centralization project developed by the Spanish Army. The main objective of the tool is to collect, analyze, structure, and visualize explicit and tacit knowledge about maintenance operations. As described before, explicit knowledge is represented by the collection of official handbooks. In contrast, tacit knowledge comes from the filmed videos of the experts performing tasks and the information from participating in a written focus group. The tool combines both resources, allowing users to interact with them and eventually annotate and modify the data based on their experience.

The tool offers two different interfaces: task- and doc-centered. The task-centered interface (see Figure 3) shows the videos of the experts performing the task from two different perspectives: first-person and third-person. It also includes a general description of the task (see the section *Description* right below the videos in Figure 3) and a detailed explanation of the sub-processes and actions included in the operation (see the accordion green menu in the lower part to the left in Figure 3). The user can also explore the knowledge base related to the task, which is represented as a force-directed graph. This type of graph is one of the most commonly used for visualizing knowledge models like ontologies [18], where the nodes are the concepts, the edges are the relations between concepts, and the colors define the hierarchical categorization of the concepts (i.e., operations, sub-processes, and actions). The visualization is integrated into the VA tool (see the lower part to the right in Figure 3) and is also available as a stand-alone interface (see Figure 4). In the stand-alone interface, users can interact with the graph, looking for a concept (see the search bar in the upper part to the left in Figure 4) and accessing tacit and explicit resources associated with a concept.

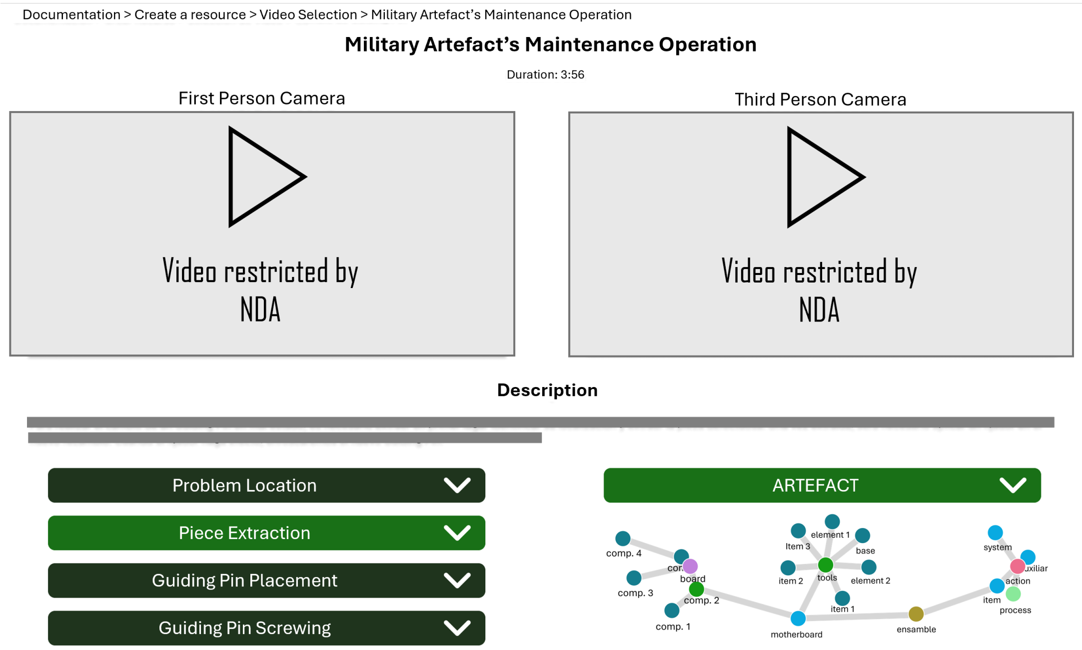

Figure 3: The task-centered interface of the proposed VA tool for knowledge transfer with the video shown in first-person and third-person, a description of the task, a list of the sub-processes and actions, and a graph of concepts and relations of the knowledge base included in the task. The images have been removed due to a Non-Disclosure Agreement (NDA) signed with the Spanish Army.

Real users could not yet evaluate the VA tool since this was an exploratory project. Still, it was presented and discussed in a focus group with officers involved in the future implementation of this kind of tool, including those responsible for this project. Moreover, expert users evaluated different visualizations of the contents, validating the different alternatives shown to them. Given the confidential and critical nature of the information involved and the need to trust the results, using generative AI tools was not acceptable to them. In contrast, the ability to see the underlying knowledge structure was valued as a useful aid in understanding the concepts and their relations in a specific maintenance operation and detecting missing information.

The doc-centered interface (see Figure 5) is an interactive PDF reader for the official handbooks. The users can go through the content of the books, add annotations based on their own experience, and check the annotations from other experts. The text is also labeled by the concepts and relations in the knowledge base (see the concept highlighted in blue in Figure 5). This labeling mechanism aims to connect the official sources and the tacit knowledge through expert videos. In this way, the user can click on a label describing an operation and see the videos of its execution. The video viewer offers the recordings from the three points of view: first-person camera, third-person fixed camera, and third-person tracking camera. The users can choose one of them or see all of them simultaneously, and they can also play, stop, change the volume, and enable the subtitles.

5. Conclusions and Future Works

Knowledge externalization and transfer are complex tasks for organizations focused on maintenance operations. The insights and know-how employees gain while performing a specific task are valuable for guaranteeing efficiency and effectiveness in terms of productivity costs, decision-making, and problem-solving. For this reason, there is a growing interest in designing strategies for externalizing tacit knowledge and its integration with explicit knowledge.

Based on existing models in the literature to formalize how the knowledge flows from humans to machines and vice versa in a VA tool, in this paper, we propose introducing an ontology as a

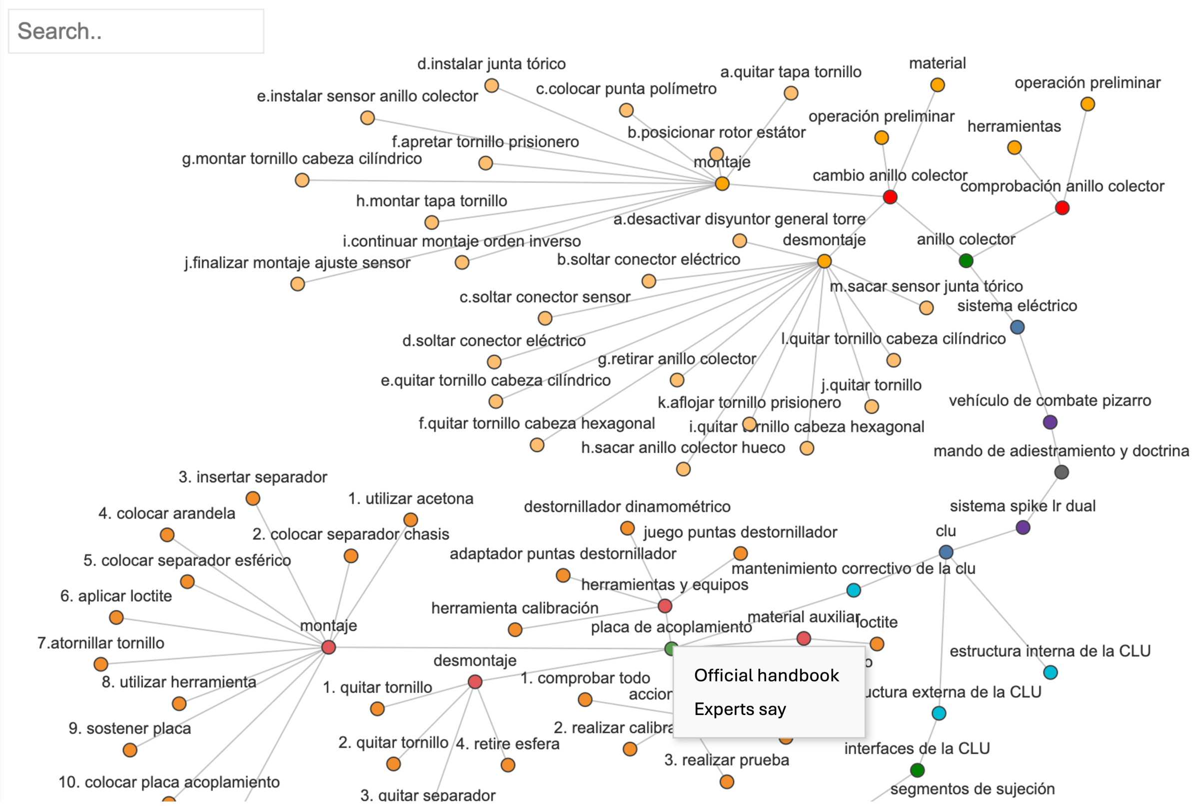

Figure 4: The knowledge base visualization as a force-directed graph with a search bar and the possibility to access the explicit knowledge (official handbooks) and the tacit knowledge (expert videos) associated with a concept.

formal structure to collect all the knowledge. This solution creates a strong association among all the information, insights, and practices that can be used to integrate human knowledge. In collaboration with the Spanish Army, we designed a VA tool to support the transfer of tacit knowledge between officers, technicians, and other employees to create an institutional memory that will guarantee that knowledge is not lost when employees leave their duties. The externalization of knowledge is achieved by filming the experts performing tasks and describing aloud what they are doing, as well as moderating a focus group where experts are asked to annotate the handbooks, including the tips, tricks, and additional tacit knowledge required to perform the tasks properly. Our results showed a good reception of both solutions. On the one side, using the HMD was considered light and not invasive to wear. On the other hand, participation and contribution in the focus group were relatively high and productive.

The knowledge base proposed in this paper represents an AI strategy to integrate explicit and tacit knowledge by creating an association through the concepts and relations already in the base, with the personal expertise added by users. In future works, we plan to extend the use case to involve more Spanish Army departments to test the proposed strategy's practical validity on a broader scale and evaluate the tool's acceptance and usability. Another promising direction for future work involves examining how generative AI (genAI) models could support the enrichment of the knowledge base, particularly by extracting structured information from manuals or analyzing videos and texts. However, two important constraints must be considered here: trust and confidentiality. First, any AI-generated suggestion must be clearly linked with a specific and verified human contribution to be trusted by maintenance personnel, as annotations or recommendations lacking an identifiable human source may not be adopted in practice. Second, many of the manuals and visual resources contain confidential information, limiting the extent to which external services or cloud-based AI platforms can be used. To comply with these restrictions, genAI capabilities should be embedded in secure, local environments where both data and inference processes remain fully under organizational control. The use of genAI

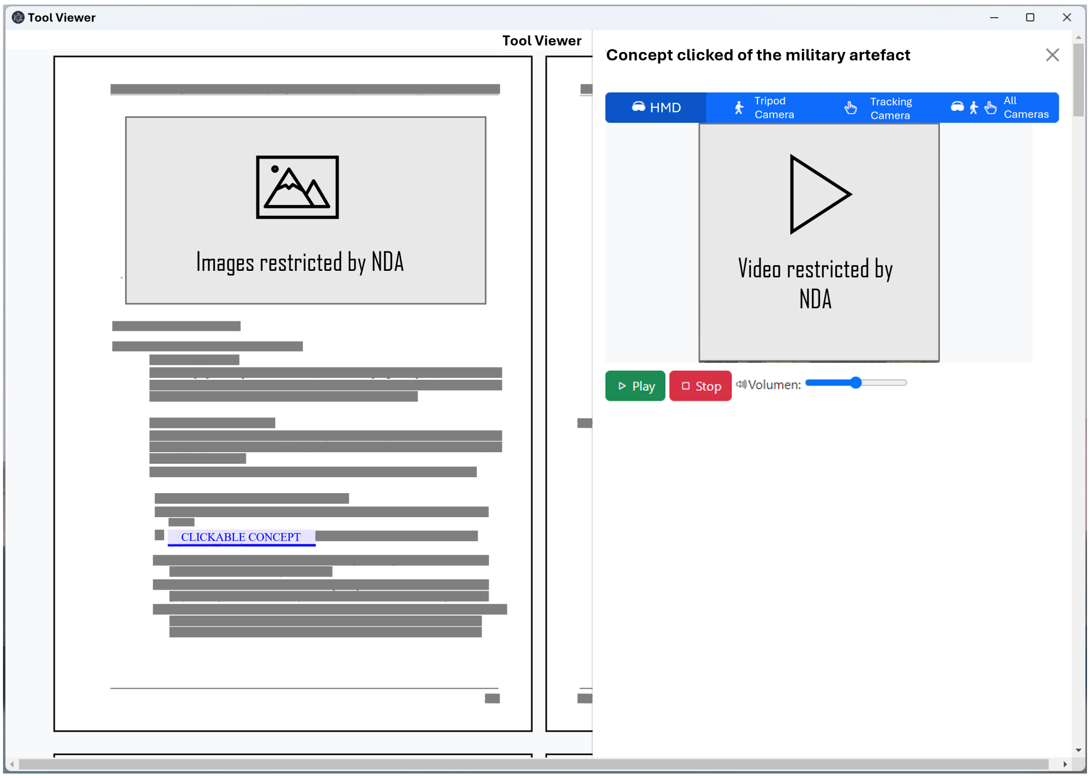

Figure 5: The doc-centered interface of the proposed VA tool for knowledge transfer. The images and the texts have been removed due to a Non-Disclosure Agreement (NDA) signed with the Spanish Army.

is not intended to automate the generation of tacit knowledge. Its purpose should be to augment the knowledge curation process while keeping experts at the center of validation and decision-making to ensure the system is reliable, transparent, and grounded in operational reality.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check, Paraphrase and reword. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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