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Methodology for augmented reality-based adaptive assistance in industry

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A B S T R A C T

Industry 4.0 technologies are key elements for companies' competitiveness. Among these technologies, Augmented Reality (AR) already shows great potential and results to assist workers through a large panel of industrial processes. Latest research suggests that AR systems should meet the user's needs to deliver a personalized experience and therefore improve the adoption of the technology. Nevertheless, there is still a lack of theoretical guidance to design AR-based assistance capable of delivering both the right level of details of information and the best information design, based on the user's needs. To address this problematic, we developed a methodology describing the principle of adaptive assistance as well as standard characteristics and criteria to design Augmented Reality-based Adaptive Assistance Systems (ARAAS). We applied this methodology on an industrial maintenance use case in the context of landing gears' overhaul operation. The feedbacks from different profiles of inspectors underline the usefulness of such system and its capacity to deliver an assistance adapted to their needs.

1. Introduction

Augmented Reality (AR) is a technology that superimposes virtual elements on the real environment in real time (Azuma et al., 2001). The superimposition of the information directly over the real environment helps operators to understand the tasks (Hou and Wang, 2013). The information is spatially contextualized based on the real environment geometry or the real part/assembly location in this environment. Moreover, the possibility of having information always displayed in the user field of view minimizes attention switching. The user does not have to spend energy and mental resources to seek information. During the past decades the development rate of AR has increased, thus this technology is now used in many fields of activity. Among these fields, manufacturing and maintenance have been using AR for a large variety of applications. Assembly and disassembly operations (Wang et al., 2022) are largely represented followed by inspection, repair, and training (Palmarini et al., 2018).

Many AR applications show good results in terms of task performances and user cognitive workload compared to traditional guidance supports such as paper-based instructions. The diminution of mental workload is the most observed gain when using AR systems (Jeffri and Awang Rambli, 2021). The AR also often improves the tasks performances. Hou et al. (Hou and Wang, 2013) compared performances of AR training to manual training on a LEGO assembly task. The results show an improvement in both completion time and error rate for both gender of participants. Bode (Bode, 2019) also demonstrated the benefits of AR in terms of completion time and accuracy observing the learning curve of a truck assembly task.

However, other studies presented contradictory results with AR leading to an increase in completion time and cognitive workload (Drouot et al., 2022). Indeed, if the working environment has big dimensions, the spatialization of the information can force the operator to locate the information, leading to extra time consumption. Ariansyah et al. (Ariansyah et al., 2022) have shown that using AR can lead to some extra cognitive workload. This can happen if the amount of information presented to the user becomes too important. Better design and attention to the quantity and type of information delivered by the AR system could avoid or at least minimize this extra cognitive workload and unlock the potential of AR assistance. Moreover, Wiedenmainer et al. (Wiedenmaier et al., 2003) suggest that the potential benefits of AR are greater when the complexity of the task raises. Radkowski et al. studied the impact of task complexity on AR instructions' design (Radkowski et al., 2015).

If AR is certainly mainly used to ease the understanding of operations instructions, it could also be used to transfer the knowledge form expert to newcomers. Nevertheless, it represents a big challenge because the system should be able to use suggestions from experts to improve its knowledge. Another challenge is to design a system that is user-friendly

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enough to be easily used daily. This is why the user's acceptance is a key element to achieve a successful deployment in industrial workshops (Syberfeldt et al., 2015), otherwise it will not guarantee the use of AR on a long-term period, and it will compromise the development and deployment of the technology for the rest of the company's activities.

Researchers have already experimented many different solutions architectures (see Table 1) that often shown some benefits regarding their use case. However, AR systems remain difficult to deploy on a larger scale in the industrial environment. This can come from the efforts required to transfer such new technology from scientific context, which remains well controlled, to the industrial environment and its wide range of constraints that need to be considered. Recent research (Geng et al., 2020; Eswaran et al., 2022) also points to the direction of adapting more the content and the global experience of AR-based assistance accordingly to each profile of worker, regarding their skills, knowledge and work preferences in order to improve the perception of the technology and thus, to ease its diffusion across the industry.

Therefore, in this paper, we are exploring the possibility to develop AR-based adaptive assistance systems (ARAAS) that can adapt the content they provide, based on workers' characteristics such as their performances, their cognitive workload and their preferences in term of working method, information visualization or way to interact with the system. This paper is organized as follow: The Section 2 presents the different approaches of AR-based adaptive assistance system already existing in the literature. The Section 3 synthesizes the limitation of existing systems and methodologies while suggesting improvements that may help to develop and deploy AR-based adaptive assistance systems in industrial maintenance context. The Section 4 presents the methodology proposed to address the limitations mentioned in Section 3 by providing guidelines to help developing and designing AR-based Adaptive Assistance Systems (ARAAS). The section 0 illustrates the application of the suggested methodology on an industrial maintenance use case. Finally, the section 6 brings some conclusion and future direction related to the proposed methodology and the remaining question concerning the adaptive maintenance assistance.

2. Related work in adaptive assistance

An augmented reality-based assistance system should consider the operators' characteristics to manage their cognitive resources by providing a support adapted to their profile (Ariansyah et al., 2022). Indeed, the Multiple Resources Model (MRM) presented by Wickens (Wickens, 2002) illustrates the limitation of cognitive resources and describes the allocation of these resources. This limitation induces a need for a good management of these resources to limit the risk of cognitive overload and thus the degradation of user's performances. However, this cognitive workload-based approach is not the only one investigated by researchers. Indeed, several studies, like the following ones, already suggest adapting the information types used in augmented reality assistance systems depending on the use case target and user's profile.

The system developed by Geng et al. (Geng et al., 2020) uses performances and preferences data from the user to determine a level of expertise to associate with the user. The system then uses this level of expertise and the current state of the task executed by the user to calculate a guidance strength requirement suited for this context. Each information mode (i.e. text, audio, picture, static annotation, static 3D model, video, dynamic annotation, and dynamic 3D model) has a corresponding guidance strength level so the system can use the appropriate information mode. The results show a good acceptability of this approach from the users, regardless of their level of expertise.

Radkowski et al. (Radkowski et al., 2015) suggest that the information modes should be selected regarding the task difficulty. In their study, they choose to restrain the use of 3D models to simple tasks because this kind of information mode requires a lot of cognitive resources. In opposite, when the tasks are getting more complex, they prefer to use schematics or text instruction because the amount of information to process is already important due to the task complexity. However, this balance between task complexity and information mode's cognitive resources consumption does not seems to be the only parameter to drive the selection of information mode. For example, Engelke et al. (Engelke et al., 2013) suggest also considering the operator's visualization methods preferences.

Ariansyah et al. (Ariansyah et al., 2022) studied the coupling between different information modes and interaction modes. All AR-based assistance conditions have shown significant performance improvements compared to the control group that used paper-based instructions. Animation induced a higher diminution of error rate than video, regardless of the interaction mode. However, none of the two interaction modes (manual and vocal) tested here, presented any superiority of performances improvement.

The CARAGS systems developed by Wang et al. (Wang et al., 2022) uses a vibrating wristband to provide haptic feedbacks to the user. The system uses a cognition model to suggest information modes to the user. The results show that this system induces a diminution in execution time and attention switching compared to standard AR-based assistance system or paper-based instructions.

In the methodology developed by Siew et al. (Siew et al., 2019), the adaptation ranges on four levels. Each level corresponds to different information mode. The system also provides different feedbacks to the

Table 1
Examples of adaptive systems and studies of AR instruction design.

Authors	Task (complexity)	Hardware	Trigger for adaptation	Elements adjusted by the system	Adaptation strategy
Geng et al. (Geng et al., 2020)	Disassembly (high)	AR glasses	User's performances & preferences	Information modes (text, video, audio, picture, 3D model)	Calculate a level of expertise for user. Information modes are associated to this level of expertise
Radkowski et al. (Radkowski et al., 2015)	Assembly(low / high)	AR workstation	Task difficulty	Information modes and design	Static study
Ariansyah et al. (Ariansyah et al., 2022)	Disassembly / Repair (low)	HoloLens 2	NC	Information and interaction modes	None
Wang et al. (Wang et al., 2016)	Assembly & repair (high)	AR glasses	User's cognition phase	Information modes	Sequence based on user's cognition or requests
Siew et al. (Siew et al., 2019)	Inspection & disassembly (high)	AR glasses	Eye tracking / gaze activity or user request	Information modes	Switch between 4 levels of adaptation based on manual requests or on dwell time of user's gaze in Areas of Interest
Erkoyuncu et al. (Erkoyuncu et al., 2017)	Inspection & repair (low)	Handheld device	Level of expertise	Information quantity, User interface design	More information displayed for novice

user. The transition between two levels can be manual or automated. In that case, the tracking of the user's gaze behaviour triggers the transition.

The system developed by Erkoyuncu et al. (Erkoyuncu et al., 2017), provides different interfaces and a regulated quantity of information based on operators' level of expertise. Thus, novices need to go through extra validation steps whereas experts can work quicker avoiding spending time on these steps. The results highlight an important diminution of execution time compared to paper-based instructions.

Across the identified studies related to adaptation of AR instruction design, we observe a significant variety of approaches concerning the characteristics considered as triggers for adaptation (level of expertise, gaze activity, user's performances, user's cognition phase and task complexity) as well as the strategies used to adapt the AR instructions. Despite this diversity, the information modes seem to remain the most frequent element of AR instruction that is modified to provide adaptation.

3. Stated problem

As seen in the last section, the systems and methodologies are very diverse and often specific to a single use case and/or industrial environment. That leads to difficulties to understand the reasons behind the design choices made by researchers and to difficulties to replicate developed solutions on similar use cases. These issues lead to the following question:

How to define standard characteristics and criteria that can be used to design adaptive assistance systems for a large variety of use cases in industrial maintenance environments?

To answer this question, we developed a methodology designed to provide guidelines for the modelling, design, and execution of Augmented Reality Adaptive Assistance Systems (ARAAS) in the context of industrial maintenance operations. The proposed methodology aims to synthesize the different approaches provided by previous research while providing a clear structure that could help to extend the design and use of such systems in future research.

4. Methodology

The methodology developed here is organized in three layers. The first layer (from the top of Fig. 1) represents the modelling of the elements that need to be considered to design an ARAAS. This first layer provides (elements in green in Fig. 1) the theoretical basis to characterize the maintenance operators, the maintenance operations, the maintenance instructions, and the maintenance environment in the context of the assistance to maintenance operations adapted to the operators. The second layer (elements in blue in Fig. 1) represents the process involved when designing an ARAAS. This includes all the

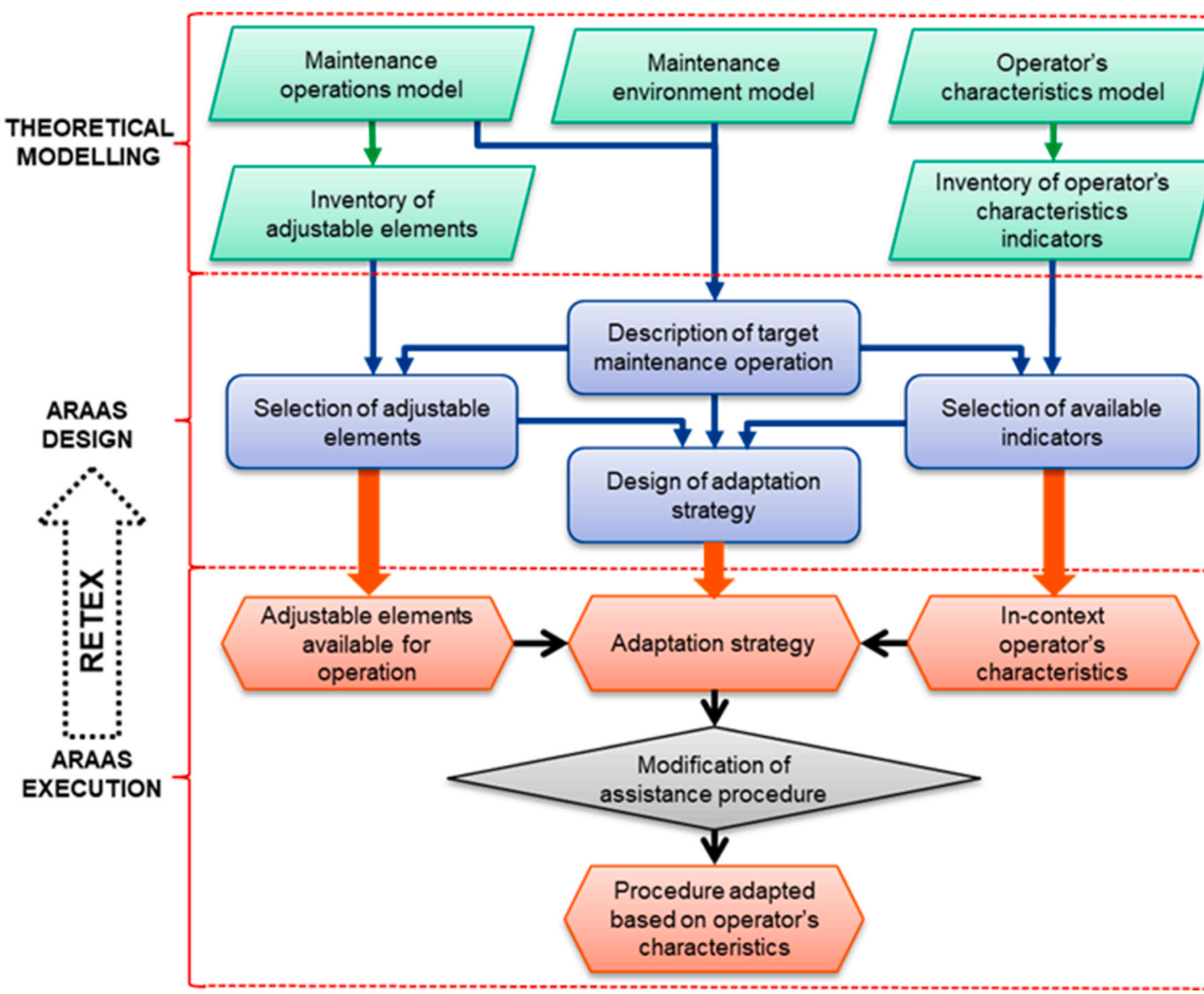

Fig. 1. Proposed Methodology for modelling, design, and execution of Augmented Reality-based Adaptive Assistance System (ARAAS).

guidelines and rules used to decide, regarding the use case considered, what the ARAAS needs to adapt, which triggers the system uses to trigger the adaptation and how the system triggers this adaptation. Finally, the third layer (elements in red in Fig. 1) details the execution of the ARAAS. Due to the high number of parameters and characteristics to consider while designing the system, this process may remain iterative. Thus, the execution of the system should be evaluated in terms of performances and user's cognitive workload management to document the return of experience (RETEX) that will feed back the design of new versions of ARAAS.

The following sections detail the concepts and processes involved in each layer. The Section 4.1 presents the first layer containing the details of the maintenance environment modelling used to design the ARAAS. The second layer is covered by the Section 4.2. This second layer is also illustrated in the Section 5 which presents the global process of ARAAS design applied to an inspection operation of a landing gear. Finally, the Section 4.3 presents the third layer that deals with the execution of the ARAAS.

4.1. Theoretical modelling

4.1.1. Maintenance operations

We define a maintenance operation as a complex process performed on a product or an equipment to control its condition and restore its structural and functional capabilities allowing its return in exploitation in safe conditions. A maintenance operation is a composite process; thus, we can divide it into smaller building blocks. We base our decomposition of maintenance operation on the work provided by Dunston and Wang (Dunston and Wang, 2008) while focusing on the operations and tasks encountered in industrial maintenance environment. Thus, a maintenance operation is composed with activities, themselves composed with tasks, which are a succession of actions. Some examples of the elements composing the maintenance operations are provided in Table 2. Dunston and Wand (Dunston and Wang, 2008) underline that mixed reality, and thus, augmented reality technologies are well suited to help operators at the task level. This is why it is important to be able to decompose the operations and activities into fundamental tasks. Indeed, identifying the tasks involved in the maintenance operations helps to understand the type of information that an assistance system should provide to the operator to execute the operation correctly. For example, if an operator must locate an element (part, tool, document, etc.) during the operation, it means that the information delivered by the assistance system must be able to describe the element to locate and the spatial relations between this element and some spatial references (e.g. the slot of a tool in a toolbox).

4.1.2. Maintenance environment

Some components of the maintenance environment can have a direct or indirect impact on the design of the ARAAS. These elements are the maintenance operation itself, including all its sub-components (as described in the previous section) and the product on which the tasks are applied. The characteristics of the product to consider when designing the ARAAS and the assistance instructions are the size of the product, the number and size of the part that eventually compose it and the number of areas of interest (AoI) on the parts. Based on the work of Quentin Loizeau (Loizeau, 2021) we identify the characteristics of the operations and products that can have an impact on the AR-based assistance experience. These characteristics of the maintenance environment, presented in Table 3, need to be considered when designing the instructions of the assistance procedure. Moreover, these characteristics give some idea of the level of complexity of the task. This is important to ensure if the task is complex enough to require a strong assistance.

Finally, it is important to include the operators, their characteristics, and their relationship with the ARAAS and the rest of the maintenance environment to understand how all the elements can influence each other (see Fig. 2).

Table 2
Examples of maintenance operations and their components.

Operations	Initial inspection, Cleaning, Disassembly, Detailed inspection, Repair, Surface treatments, Painting, Assembly, Final Inspection
↳Activities	Inspection, Assembly, Planning
↳Tasks	Identify, Locate, Select, Annotate, Connect, Measure, Report
↳Actions	Move, Grab, Hold, Eye travel, Reach

4.1.3. Operator's characteristics

The operator's characteristics considered in our model are the following: the performances, the preferences, and the cognitive workload.

These three characteristics vary from one operator to another, inducing the need for an adaptation of the content and the assistance experience provided by the ARAAS. These characteristics compose what we call the operator's profile.

The performances evaluated in industrial settings concern the temporal and quality levels achieved when completing a task. These two aspects are represented by the completion time and the error rate achieved on the task. Measuring the level of performances achieved by experts on a task provides a good reference level to compare the performances and thus, the level of expertise of on this task for other operators. The performances are evaluated at different time scale, form task to operation levels.

The preferences characteristic refers to working methods preferred by the operator to perform a task. It can concern the use of a certain tool when several tools are compatible with the action performed. It can also concern the way the operator divides the task into basic actions and the sequence chosen to perform all these actions. In the context of maintenance operations assisted by augmented reality, the operator can also manifest preferences when using the different features included in the AR-based assistance system.

The cognitive workload represents the consumption of cognitive resources induced by the execution of the task. An increase of this workload is related to stress, frustration and mental or physical fatigue induced by the task. The number and the nature of actions required during the tasks influence the evolution of this workload.

The Fig. 2 illustrates the relations existing within the maintenance environment between the ARAAS (in grey), the operator's characteristics (in green), the physical actors and elements of the workshop (in blue) and the maintenance operations components (in red). This representation illustrates the place of the ARAAS within the context of maintenance environment. Moreover all the elements represented have an influence on the design of the ARAAS (detailed in Section 4).

In addition to these characteristics the ARAAS can also the level of expertise to set up initial adaptation. The level of expertise is based on

Table 3
Maintenance environment characteristics having an impact on AR assistance.

Characteristic	Type / Levels
Number of actions	Integer
Task nature	See Table 2
Number of tools	Integer
Number of parts to identify	Integer
Number of AoI to identify	Integer
Number of parts to manipulate	Integer
Size of product	Very small (can be hold in one hand) Small (can be hold in two hands) Medium (can't be hold) Large (requires navigation around the product) Very large (navigation within the product)
Use of hands	No hands used One hand used Both hands used

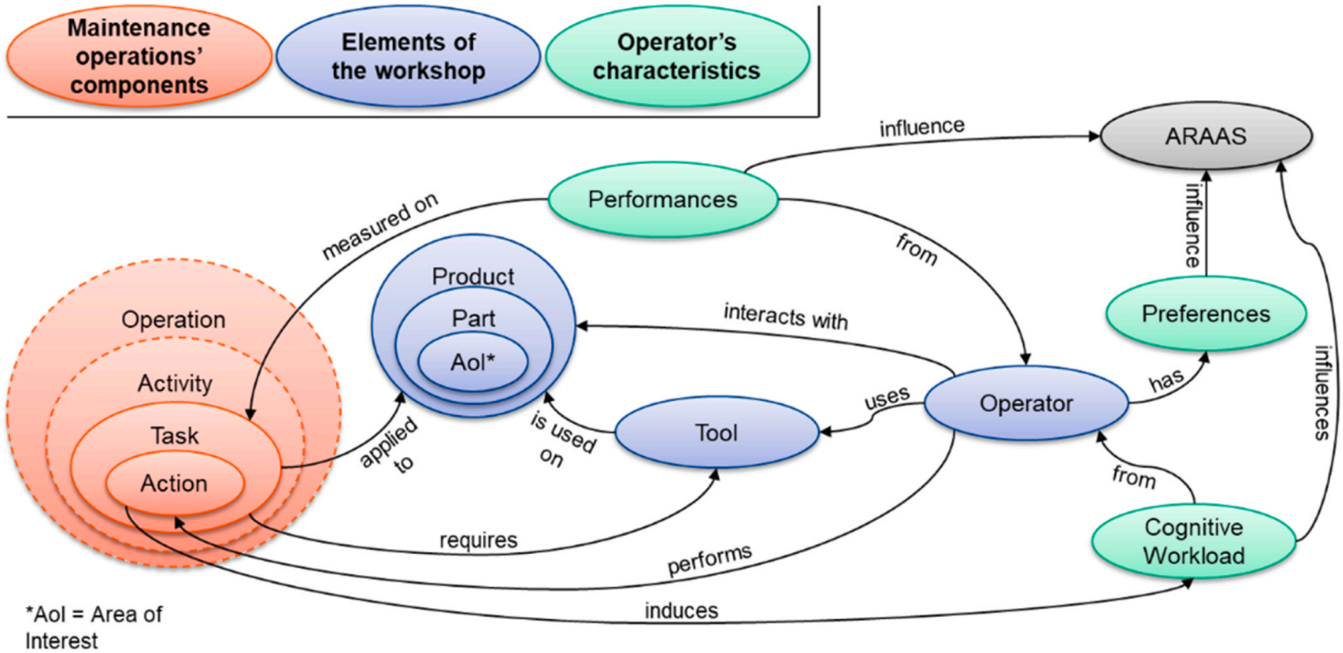

Fig. 2. Ontology of maintenance environment including ARAAS.

the combination of knowledge and skills. It expresses the ease of execution of a task by the operator. In terms of performances, this level of expertise represents the ability that an operator to achieve a high quality of work within a short execution time. The level of expertise is often evaluated in industry. It can be estimated based on subjective evaluation made by experts or it can be approximated based on the number of years of experience on the task. This notion of expertise is also related to the performances of the operator. The performances can vary from one operation to another. Thus, the level of expertise can be estimated based on the average of performances achieved on several operations.

4.1.4. Inventory of adjustable elements

The term element is here used as a reference to all kind of parameters or components of the assistance system and the procedure provided by such system. Those are all the variables the ARAAS designer can use to create a system that suits the maintenance environment constraints and answer the needs for operations assistance.

Many elements of the assistance procedure and the ARAAS itself are potentially adjustable. We can classify these elements in different categories depending on their nature or the components of the assisted maintenance environment they concern. These categories are the information delivered by the system, the structure of the assistance procedure and the system's settings. The Table 4 summarizes the different adjustable elements associated to these three categories.

4.1.4.1. Information delivered by the system. The first category of adjustable elements is related to the information displayed by the ARAAS. These adjustable elements are information modes, information design, information quantity, information redundancy and information availability.

Table 4
Adjustable elements the system can modify to adapt the assistance to the operator.

Information delivered by the system	Structure of procedure	System settings
Information modes	Number of steps	Input modes
Information design	Information density	Adaptation rate
Information quantity	Order of steps	Request management
Information redundancy		System feedbacks

The information modes that are often used in the context of AR assistance for manufacturing and maintenance processes are the following: text, pictures, technical drawings, pictograms, audio, video, static 3D models and dynamic (animated) 3D models. These information modes can be associated to specific functions or actions required during task execution (Li et al., 2019). Moreover, information modes have not the same impact depending on user's level of expertise (Geng et al., 2020). Engelke et al. (Engelke et al., 2013) suggest that user's visualisation preference should also be considered when delivering augmented reality-based assistance.

The information design also has an impact on the experience provided to the operator and thus, his performances (Gatullo et al., 2015). The system can adjust the opacity or the colour of 3D models or text displayed in order to remain easily visible for the operator regardless of the lighting conditions.

The quantity of information provided by the system can be defined based on the operator's level of expertise. Indeed, a beginner will benefit from detailed information whereas too much information could slow down more experienced profiles. Expert do not want to have to sort critical information from what they already know about the task or the product affected by the task.

Similarly, including information redundancy can provide an additional support for learning purposes but can also represent a constraint for more experienced operators. The information redundancy can also emphasize a special action or bring the focus on warnings.

The information availability can also be adjusted between having the information always displayed and delivering it on-demand (Kim et al., 2019). This design choice should consider the degree of freedom given to the operators to choose what information they can access, having in mind that too much freedom can induce cognitive workload to seek information.

4.1.4.2. Structure of the assistance procedure. The second category of adjustable elements of the ARAAS concerns the structure of the assistance procedure. Since operations and activities are a succession of tasks which are themselves a succession of actions, the associated process is often described as a sequence of steps. The adjustable elements of this sequence are the number of steps, the information density, and the order of steps.

The number of steps can vary depending on the nature of the task and activities. Assembly activities can have many steps since a lot of different actions are often required to complete the assembly while inspection activities procedures are more often less detailed, unless a specific checklist is provided to the operator. Nevertheless, the sequencing and therefore, the number of steps can sometimes be modulated regarding the level of expertise or the preferences of the operator (Novick and Morse, 2000).

The information density represents the amount of information contained in a single step. It should be regulated to avoid overflowing the operator's processing memory. Therefore, information density should remain low for inexperienced operators (Novick and Morse, 2000) while it can be preferable to increase it for more experienced ones.

The order of steps should be adjusted according to operator's preferences in terms of working strategy. Indeed, some operators may prefer to group the actions and tasks to perform based on their nature, the tools required or the location of their application. However, some tasks such as those found in assembly have strong planning constraints and thus, the order of steps should not be altered to complete the task correctly.

4.1.4.3. System settings. The third category of adjustable elements are the settings of the ARAAS itself and have nothing to do directly with the content of the assistance procedure. These system settings are the interaction modes, the adaptation rate, the requests management, and the system feedbacks.

Input modes can be adjusted according to the operator's preferences. Wickens (Wickens, 2002) suggests that mixing input modes (e.g. gesture and voice command) could improve users' cognitive resources allocation and their performances on the task.

The adaptation rate is a key parameter of the ARAAS as it defines when the system will update the assistance procedure. This adaption rate can take many values. However, among all these possibilities, two main behaviours stand out. Indeed, depending on the adaptation rate's definition, the modification of the procedure can occur while performing the task or between working sessions.

The management of operators' requests is another element that the system can adjust to provide operators more control on their assistance experience. The system can also restrain the requests possibilities to avoid operators wasting their time exploring the possibilities offered by the system.

To improve the involvement of the operators during task execution, the system can provide different feedbacks (e.g. visual, audio or haptic). However, it remains important to be able to modulate these feedbacks to avoid distraction of the operators. Thus, the system should be able to use the good combination of feedbacks modes and to adjust their frequency.

4.1.5. Inventory of operator's characteristics indicators

To adjust the content and the settings to the characteristics of the user, the ARAAS must be able to evaluate these characteristics while the user is performing the task. There are many ways to measure these characteristics (Fig. 3).

4.1.5.1. Performances. The performances are widely measured in industrial setting because the indicators used to do so provide a good representation of the industrial system's efficiency. The performances are evaluated from a time consumption and quality perspectives. The indicators related, called KPI for Key Performance Indicator, are the execution time and the error rate.

4.1.5.2. Cognitive workload. The cognitive workload of user relates on the demand imposed by a task on the cognitive resources (Wickens, 2008). The easiest way to evaluate this workload is using subjective evaluation methodologies, typically questionnaires. Users make self-assessment of the perceived demand of the task. This kind of evaluation can be completed by objective measurement. These measurements corresponds to the monitoring of several physiological activity parameters that can translates variations of cognitive workload.

4.1.5.2.1. Questionnaires. The first type of indicator widely used to assess the users' cognitive workload are questionnaires. Among all the custom questionnaires provided by different research teams, the most used today remains the NASA-TLX (Hart and Staveland, 1988). This questionnaire has been used across many studies in the past decades (Hart, 2006). This history brings strong cues concerning the confidence in the capability this questionnaire has to assess the cognitive workload properly. Despite having a good ability to assess user's cognitive workload and being easy to deploy, this type of questionnaires remains highly subjective due to their methodology relying exclusively on self-assessment from the user. To provide stronger assessment, it is possible to use objectives indicators related to the user's physiological activity.

4.1.5.2.2. Gaze activity. The gaze activity provides good cues to assess the cognitive workload of the user (Ahlstrom and Friedman-Berg, 2006). The mean value of the pupils' diameter increases when the cognitive workload increases. A diminution of blink duration also correlates to an increase of cognitive workload.

4.1.5.2.3. Heart activity. The heart activity data can be analysed through the temporal or the frequency domains. The Heart Rate Variability (HRV) remains the most used indicator form heart activity monitoring for the evaluation of cognitive workload (Charles and Nixon,

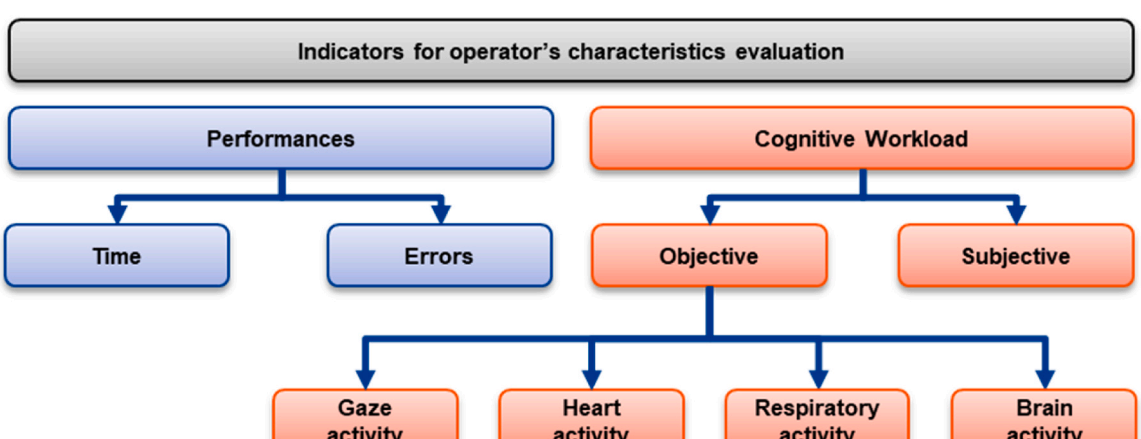

Fig. 3. Mapping of the indicators used for the evaluation of user's profile.

2019).

4.1.5.2.4. Electro-dermal activity. Some signals of skin conductance activity provide interesting cues to evaluate cognitive workload. However, these signals are sensitive to various environmental factors such as daytime, seasons, temperature, or humidity (Charles and Nixon, 2019). Therefore, we do not recommend these indicators for a use in an industrial environment where the repeatability of the measurements in various conditions is a key element.

4.1.5.3. Synthesis. The observed correlation between the evolution of each indicator and the corresponding increase in cognitive workload obeserved is synthesized in the Table 5. This table also provides an overall estimation of the reliability of each indicator in an industrial context. The reliability is estimated based on the sensitivity of the indicator to variations of other parameters than those related to the operators' cognitive workload reported in other studies (Charles and Nixon, 2019). We attribute a grade to the reliability on a 3-levels scale (0: the indicator is not reliable due to important sensitivity to external parameters, 1: the indicator may not be always fully reliable depending on specific tasks requirements or environmental condition, 2: the indicator is reliable in most of the cases).

4.2. ARAAS design

4.2.1. Description of target maintenance operation

The first step of the ARAAS design process is to describe the target maintenance operation and environment through their characteristics that can have an impact on the choice of the ARAAS components. Based on the decomposition of the operations presented in Section 4.1.1, it is important to identify the tasks and actions that compose the target operation. Indeed, each type of task involved in the operation requires different types of information to be understood and to be correctly executed by the operator. The characteristics identified in the Section 4.1.2 must be evaluated to select the adjustable elements that the system can use and to understand which among them may have the most impact on the overall assistance experience. The link between these characteristics and the selection of the adjustable elements is detailed in the next section.

In addition to these task characteristic, the following five must also be evaluated: the physical demand, the verbal communication, the mobility, the task duration, and the ethical considerations. The physical demand represents the physical effort induced by the actions required to perform the task like manipulating, moving, or lifting. The verbal communication concerns the tasks that require speech. The mobility translates the amplitude of the movements the operators must execute to perform the task. It ranges from the manipulation of small parts to the navigation of the operators in the workshop. The task duration is the mean time needed to complete the task. Finally, the ethical considerations characteristic represents the hardness of the company policy concerning operators' instrumentation and personal data collection. The Table 6 provides possible levels for these five characteristics and parameters influencing their evaluation.

4.2.2. Selection of adjustable elements

The selection of adjustable elements for the target maintenance operation is based on the description of this operation and the relation between operation's characteristics and adjustable elements (see Table 7). The number of tasks, parts, and Area of Interest (AoI) involved in the operation have a direct influence on the information quantity that the system must deliver to the operator. Moreover, a high amount of information can require breaking down the information stream into a sequence of smaller steps presenting a reduced amount of information at once. This is why the number of steps, and the information density are also affected by these three characteristics. The number of tools used to perform the tasks can influence the order of steps as this order could be optimised to minimize switching between tools if many are used during the operation. The information redundancy can also be used to remind the operator how to use a tool if it is only used a couple of time during a long operation. The number of parts to manipulate and the use of hand must be considered when selecting the interaction modes available for the operator. Indeed, if the operation requires intensive use of hands and manipulating many parts, voice command may be preferred to interact with the system instead of manual inputs (e.g. touchscreen, keyboard or controller). The size of the product may have an impact on the information design, especially in augmented reality. Especially, the information should be presented differently depending on the position to operator relatively to the part because, if the part is large, small visual cues useful in narrow areas may not remain visible when the operator steps back to have an overview of the part.

Finally, this selection is also influenced by the nature of tasks that compose the operation. For example, the task "identify" implies that the operator must recognize an element (e.g. a part, a tool or a feature). Thus, the information design should not induce visual occlusion that could prevent the operator from identifying the element correctly. The information modes used should also be selected according to the easiest and most efficient way to deliver the information based on the nature of the tasks. If the operator must "locate" something during the operation, it will be easier to present the location using augmented reality rather than describing it with textual instructions.

4.2.3. Selection of available indicators

Of course, many constraints influence the capability to deploy and use some of the indicators presented. These constraints affect the capability to use the different indicators at different levels. Based on

Table 5
Evolution of indicators corresponding to an increase in Cognitive WorkLoad (CWL).

	Indicator	Indicator's evolution corresponding to an increase of cognitive workload	Reliability
Gaze activity	Pupil diameter (D_p)	$D_p \nearrow \equiv CWL \nearrow$	2
	Blink duration (d_b)	$d_b \searrow \equiv CWL \nearrow$	2
Heart activity	HRV	$HRV \nearrow \equiv CWL \nearrow$	2
	IBI	$IBI \searrow \equiv CWL \nearrow$	1
Respiratory activity	Respiration rate (f_r)	$f_r \nearrow \equiv CWL \nearrow$	1
	Respiration volume (V_r)	$V_r \searrow \equiv CWL \nearrow$	1
Brain activity	P300 amplitude	$P300 \searrow \equiv CWL \nearrow$	2
	α power (P_α)	$P_\alpha \searrow \equiv CWL \nearrow$	2
	β power(P_β)	$P_\beta \nearrow \equiv CWL \nearrow$	1

Table 6
Evaluation of characteristics having an impact on indicator's selection.

Physical demand	Manipulation rate, size of equipment, weight of manipulated equipment
Verbal communication	Chat complexity, communication rate
Mobility	0 – no significant movement required 1 – limited navigation 2 – navigation around equipment 3 – navigation between stations 4 – navigation around facility
Task duration	0 – a few seconds 1 – a few minutes 2 – a few dizains of minutes 3 – a few hours 4 – more than a shift (8 h)
Ethical considerations	0 – no specific consent required 2 – operation consent required once 4 – operation consent systematically required

Table 7
Adjustable elements impacted by task characteristics.

Characteristic	Adjustable elements mainly impacted
Number of tasks	Number of steps
Number of parts to identify	Information quantity
Number of AoI to identify	Information density
Tasks nature	Information modes
	Information design
	Information redundancy
Number of tools	Information redundancy
	Order of steps
Number of parts to manipulate	Interaction modes
Size of product	Information design
Use of hands	Interaction modes

technical considerations of sensors implementation and the conclusions of Charles et al. (Charles and Nixon, 2019), we classified the impact of tasks characteristics on the capability to monitor and exploit the data from the different physiological activity components to assess cognitive workload. The rating scale is a three level Likert scale (0: low impact, 1: moderate impact, 2: high impact). The coefficients of the matrix represented by Table 8 are the impact factors, noted $IF_{i/\varphi}$, representing the impact of a task characteristic i on a physiological activity measure φ. These task characteristics are those defined in Section 4.2.1.

In our model, we consider the evaluation of task characteristics on a five level Likert scale. This evaluation can be conducted through a questionnaire submitted to experts on the target maintenance operation. The experts assess the level α_i of each relevant characteristic i on the task. These characteristics can also be evaluated by referring to the guidelines provided in Table 6.

The results of these assessments are then used in combination with the corresponding impact factor $IF_{i/\varphi}$ to calculate the impact level $I_{T/\varphi}$ induced by a task T for each physiological activity measure φ. This score is calculated using (1).

$$I_{T/\varphi} = \sum_{i=1}^{n} IF_{i/\varphi} * \alpha_i \quad (1)$$

with n being the number of task characteristics.

To decide which physiological activity measurement is the most suitable regarding the target maintenance operation, the normalized impact score of the task, noted S_φ, is calculated for each type of measure φ using (2).

$$S_\varphi = 1 - \frac{n}{I_{T/\varphi}} \quad (2)$$

The lower the score, the better the compatibility of the physiological activity measure φ with the target maintenance operation's context. The results obtained with this method should not be considered as an absolute truth but only as cues to decide which indicator to use in a specific use case. Moreover, to have the most accurate and robust evaluation of the user's cognitive workload, it is recommended to use several indicators. Indeed, the information gathered by the monitoring of different indicators can be compared to assess the validity of a statement about user's cognitive workload. Therefore, it is possible to consider the use of several indicators whose scores are similar. The application of these formulas is illustrated in Section 5.3.

4.2.4. Design of adaptation strategy

The adaptation strategy is a set of rules that link the characteristics of the operators with the adaptation of the content and overall assistance experience that the ARAAS will offer to the operators. The first step when designing an adaptation strategy is to define which operators' characteristics will influence the different adjustable elements of the ARAAS that have been identified earlier. Based on the results of the different studies identified in Section 2 we can provide guidelines (see Table 9), for each adjustable element, to decide which operators' characteristic should have the most influence when triggering the adaptation of the element. Note that the level of expertise mentioned in Table 9 covers the notion of performances and cognitive workload as these characteristics can be used to assess this level of expertise. This level can also be initially assessed by dedicated questionnaires.

4.3. Execution of the system

The adaptation principle is based on three main components: The adjustable elements of the assistance procedure and the system, the indicators used to monitor the operator's profile, and the adaptation strategy driving the ARAAS. The adjustable elements are the components of the assistance procedure or settings of the ARAAS that can be modified at runtime or between work sessions. The ARAAS is free to modify them only if it can do so without altering the feasibility of the task. Indeed, an important rule to decide which element the ARAAS can adjust is to check if it's still possible to perform the task if the considered element is modified. The indicators used to monitor the operator's profile are used by the ARAAS to assess the performances, the preferences, and the cognitive workload of the operator. Thus, these indicators provide cues on the level of assistance needed for the operator. Finally, the adaption strategy refers to the system of rules linking the input data of the operator's profile to the response that the ARAAS should provide.

5. Application to a landing gear maintenance environment

5.1. Description of target operation

To illustrate how to use the methodology in an industrial setting, we

Table 9
Main operator's characteristics as adaptation trigger for each adjustable element.

	Adjustable element	Level of expertise	Preferences
Information	Information modes	X	-
	Information design	-	X
	Information quantity	X	-
	Information redundancy	X	-
Structure of the procedure	Number of steps	X	-
	Information density	X	-
	Order of steps	-	X
System settings	Interaction modes	-	X
	Adaptation rate	X	-
	Requests management	-	X
	System feedbacks	X	-

Table 8
Impact factors of task characteristics on physiological activity indicators used to assess cognitive workload.

	Physical demand	Verbal communication	Mobility	Task duration	Ethical considerations
Gaze activity	0	0	0	2	1
Heart activity	1	1	0	1	1
Respiratory activity	2	2	2	2	2
Brain activity	0	1	1	0	2

applied our methodology to a real-life industrial maintenance use case in a landing gears' MRO (Maintenance, Repair, and Overhaul) workshop. The maintenance of landing gears requires their disassembly and several inspection operations. Among all the components composing the landing gear assembly, the structural parts are the most complex in terms of geometry and mechanical constraints. Thus, the inspection of these components, such as the main fitting (visible on Fig. 4), is a critical operation of the overhaul process. The inspectors must deal with a wide amount of information to inspect and decide if they must repair or scrap the part. During the visual inspection of the part, the inspectors must measure specific areas, typically the holes, and must check if the dimensions measured stay within the tolerances defined in the technical documentation (the CMM for Component Maintenance Manual). Since it is impossible for the human brain to memorize the amount of information required to complete the inspection of the main fitting, the operators must seek information in the CMM, which can be time consuming and mentally exhausting. Thus, the assistance application uses augmented reality to show the areas concerned by the CMM tolerances and their corresponding values. In that way, the operators know what they need to inspect, where the areas are located on the part, and the decision to make when measuring areas. The hardware chosen for the system presented in this section is a Microsoft Surface Pro 7 tablet. This choice has been made based on the need to navigate around the main fitting which is about two meters long. The AR application is based on DIOTA player solution, the industrial AR solution already used by the MRO workshop.

As mentioned in Section 4.1.1, the first step when describing an operation is to decompose it into fundamental tasks to identify the information the ARAAS will have to provide to the operator. During this inspection operation, the operator must locate some areas to measure their dimensions. The operator must then annotate the result of these measurement. Finally, the operator must identify the tolerances associated to the area measured to decide if the part must and/or can be repaired. Therefore, the information that the system must deliver to the operators include the areas to measure/inspect and the corresponding tolerances. Therefore, the ARAAS uses Augmented Reality to highlight the areas to inspect. The tolerances are presented in a 2D side panel in the AR application interface. The Fig. 4 presents the user interface in the context of a trial in the maintenance environment. To see the corresponding tolerances to a specific area, the operators only need to click on this area in the AR viewport (left of Fig. 4). In addition, the Table 10 describes the rest of the characteristics that need to be considered to design the ARAAS.

5.2. Selection of adjustable elements

The high number of actions identified for this operation induces an important quantity of information. Thus, less experimented operators should benefit from a sequential presentation of the information that limit the amount of information presented in each step of the procedure. The amount of information that the system can deliver at once may evolve with the experience of the operators and their ability to sort the information. Finally, the tasks involved in the inspection operation do not have to be executed in a precise order. This is why the system should be able to provide as much freedom as possible to the operators when deciding the order they want to tackle the different tasks. Therefore, the adjustable elements selected for the target operation are the number of steps, the information density, and the order of steps.

In addition to these technical considerations, the experts involved in the development requested a sort of digital catalogue presenting all the information at once. Since the experts already have a good knowledge of

Table 10
Task characteristics of the use case.

Characteristic	Type / Levels
Number of actions	132
Tasks nature	Identify, Locate, Measure, Annotate
Number of tools	1
Number of parts to identify	1
Number of AoI to identify	33
Number of parts to manipulate	0
Size of product	Large
Use of hands	One hand used

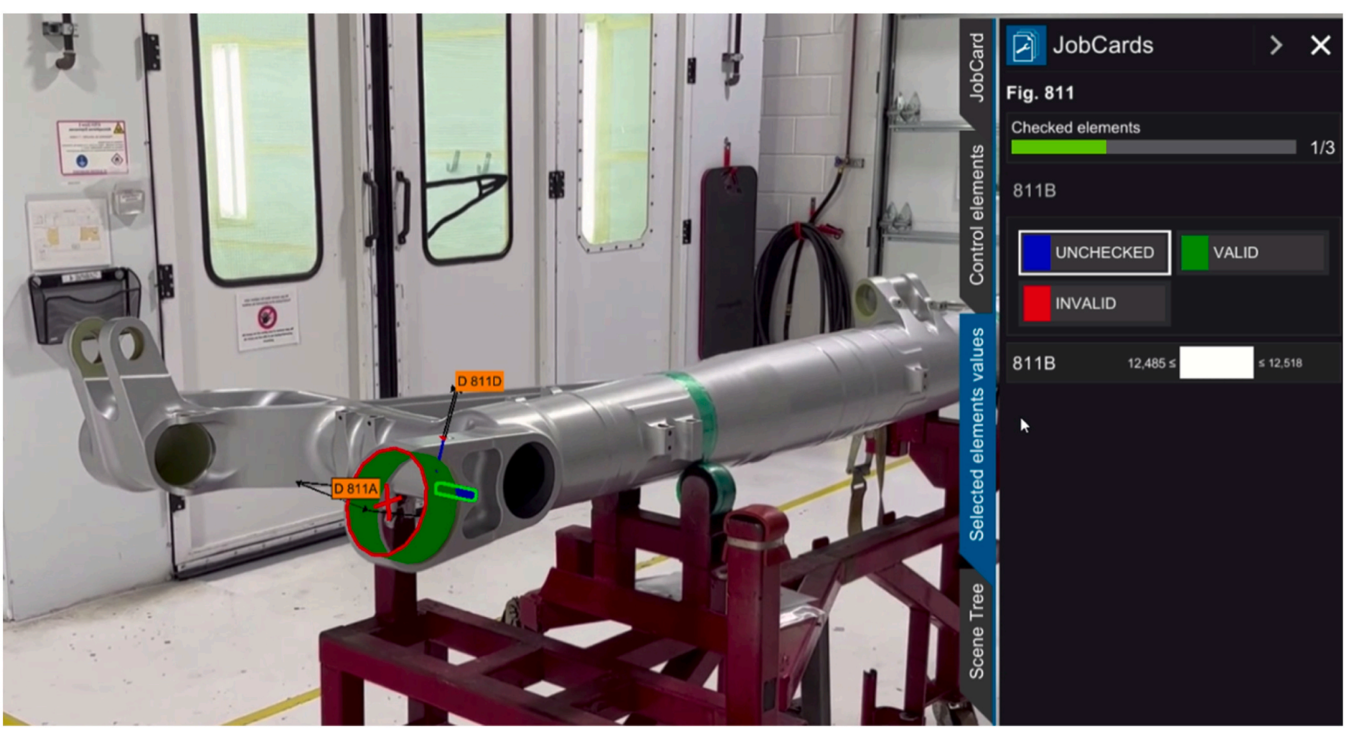

Fig. 4. Trial of the application in the maintenance environment.

the part and the areas concerned by the inspection, they can easily navigate through this information overview (right of Fig. 5). However, less experimented operators need guidance to understand where to inspect. Thus, a sequential scenario (left of Fig. 5) is designed for this user profile. In this scenario, the inspection is broken into a sequence of fifteen steps. Each steps includes a maximum of six inspection points, all included in a relatively small area of the part to avoid cognitive overload for the operators.

5.3. Selection of available indicators

The characterization of the inspection operation is made through observation of the process and interviews of experts. The rating of each characteristic is the following: physical demand$\alpha_1 = 1$, verbal communication $\alpha_2 = 0$, mobility $\alpha_3 = 2$, task duration $\alpha_4 = 3$ and ethic $\alpha_5 = 3$. We apply the formulas (1) and (2) form the section 0 to estimate and rank the relevance of each indicator for the operation studied. The scores obtained for each physiological activity's indicators are $S_{gaze} = 0*1 + 0*0 + 0*2 + 2*3 + 1*3 = 0.44; S_{cardiac} = 0.29; S_{respiratory} = 0.72; S_{brain} = 0.36$. The indicators measuring cardiac activity have the lower score, meaning that they are the most suitable for this use case to assess the operators' cognitive workload. The scores of gaze activity and brain activity indicators remain relatively close. They both could be used as a complement to enhance the reliability of the cognitive workload evaluation made by the system. Despite the constraint on mobility ($\alpha_3 = 2$), the gaze acitivity could be easily measured with eye tracker of a HMD (Head Mounted Display) such as Hololens 2. However, technical constraints form the company restrained the use of such hardware. The execution time is the indicator used to reflect the performances on the task. The navigation between the steps of the sequential scenario is recorded to understand the sequence preferred by the operator. Finally, the cardiac activity indicators are the only ones that can be used in the context of this use case and their use must be approved be the managers and the operators.

5.4. Design of adaptation strategy

Based on the Table 9 we assign an operator's characteristic as a trigger for each adjustable element identified in Section 5.2. Thus, the data related to the level of expertise are used by the system as an input to trigger adaptation of the number of steps an information density in the assistance procedure (i.e. to decide which scenario the system must launch). The data from the operator's navigation preferences are used to trigger changes in the order of steps in the sequence.(Fig. 6).

The adaptation strategy designed for this use case runs at two stages. The first stage uses the performances and, if available, the cognitive workload variation to understand if the operators are enough experimented and not to overwhelmed to use the overview scenario or if they need more guidance. If more guidance is needed, the system runs the sequential scenario. The second level of adaptation occurs when the operator is using the sequential scenario. Indeed, in that case, the navigation between steps is recorded. In that way, on the next session, the scenario will rearrange the steps to fit to the operator's preferences. If the system estimates the operator become enough experimented it will launch the overview scenario.

The Fig. 7 provides an example of two sequences of instructions displayed to the users. The sequence A is the default sequence based on the order used in the maintenance manual to present the information. This choice was made to guarantee some consistency between the old and the new process. The sequence B is a sequence generated by the system based on navigation data from previous session during which the user decided to inspect the points in an order that minimized walking around the part.

5.5. Feedbacks from operators

This system has been tested in the industrial environment by three inspectors. One of them an expert (more than a year of experience) while the two others were less experimented (less than 6 month of experience). The reception of the assistance delivered by the system was good. The three operators stated that the scenario proposed by the system met their needs and was more suited than the other one. The expert underlined the fact that the overview scenario was particularly adapted to his needs compared to the sequential one which was similar to previous AR-based assistance scenarios he experimented on another maintenance operation. Moreover, the system allowed the inspectors to avoid seeking tolerances information in the maintenance manual. The mean time saved on his task is around 41 min. That represents 10 % saving on the total inspection time, which is about 6.78 h. In conclusion, the system designed applying the methodology allowed the inspectors to improve their performances by providing an assistance meeting their needs, according to their feedbacks. In conclusion, the system allowed the operators to save time and, thus, to improve their performances while meeting their needs for assistance according to their feedbacks.

In addition to this demonstrator, we also applied this methodology to two other maintenance use cases in the same landing gear company. The first one is a paint masking operation and the second one is a preliminary inspection operation. Among the nine augmented reality projects launched in this company for at least six months, only these two use cases using ARAAS achieved more than 18 months of activity. This can

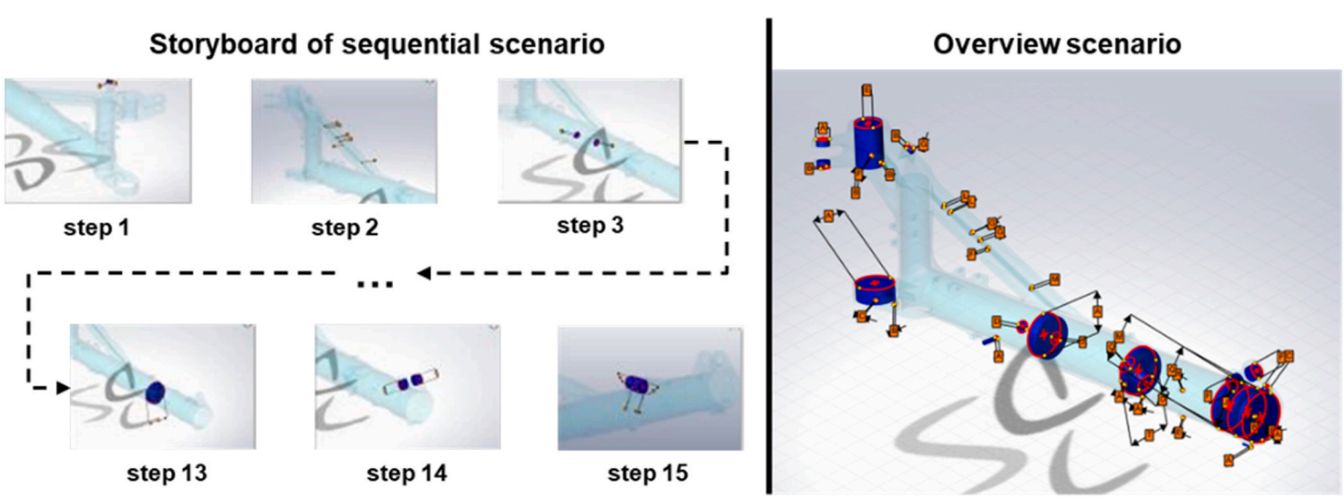

Fig. 5. The two scenarios designed for the assistance to the main fitting's inspection of a landing gear.

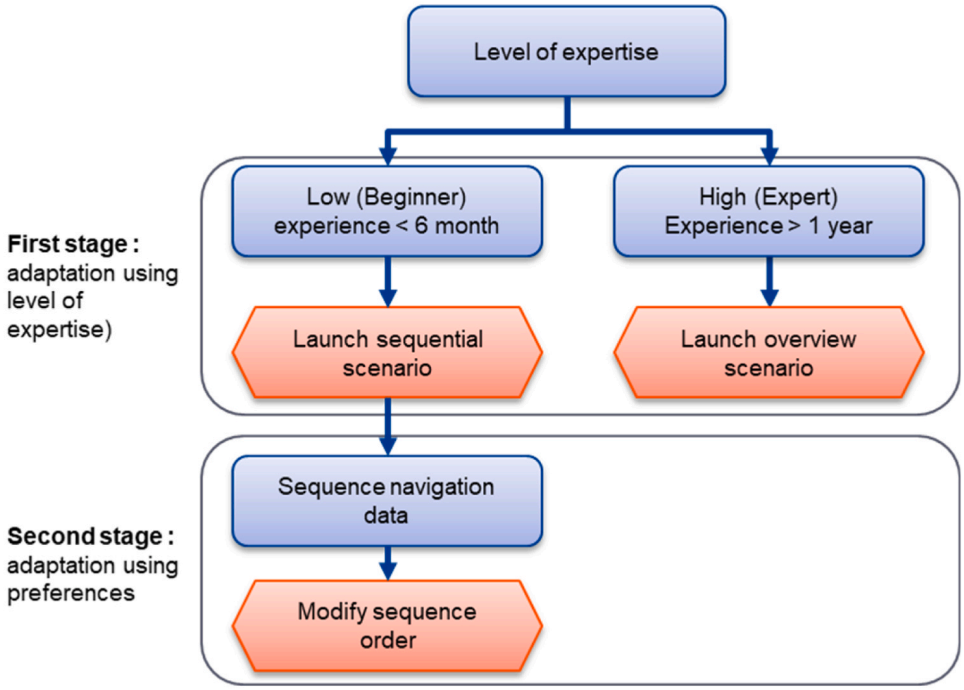

Fig. 6. The two stages of the adaptation strategy.

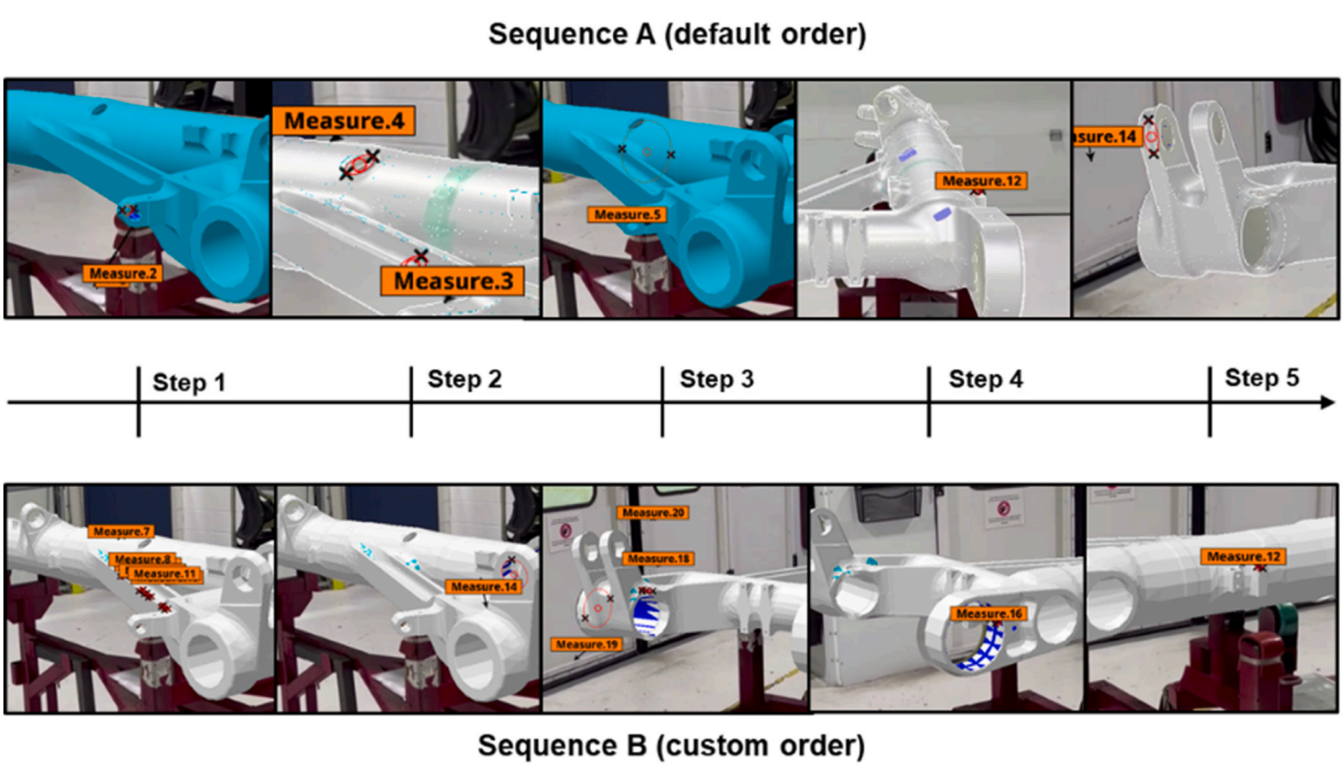

Fig. 7. Examples of sequences generated by the system.

be explained by the capacity of ARAAS to meet the user needs and their evolution on long term, and thus, its capacity to keep the operators engaged with the system. For the preliminary inspection, the execution time has been reduced up to 79 % compared to the old process that used paper and pencil. For the paint masking, the number of errors has been divided by 7. Moreover, the authoring time has been reduced by 40 %.

6. Discussion

6.1. Conclusion

The methodology presented in this paper has been developed to answer the question: How to define standard characteristics and criteria that can be used to design adaptive assistance systems for a large variety of use cases in industrial maintenance environments? We design a methodology describing the fundamental modelling of maintenance environment and operations, required to design ARAAS. The second layer of the methodology suggests some guidelines and criteria to help future ARAAS designers to create new assistance experiences or to reuse elements of systems already developed in the literature.

We demonstrated the application of this methodology to the inspection of a landing gear's structural part. The preliminary results gathered with the three operators who tested the system are encouraging. However, the results should be evaluated on a longer period (between 6 month and a year) to evaluate if the system is sustainable and if it can maintain a high level of engagement. The time scale of use of the two other use cases using ARAAS seems to indicate that the adaptation provided by such system allows to keep operators engaged on longer period than other uses cases using non-adaptive augmented reality that have difficulties to remain in service over a year.

6.2. Limitations

The number of use cases developed using the presented methodology remains low. Moreover, the use cases presented and mentioned in this paper are far from covering most of the types of maintenance operations. For these reasons other typologies of maintenance operations such as assembly, disassembly and non-destructive testing should be explored applying the methodology. Furthermore, the number of inspectors interviewed during our study is limited due to the limited inspector population in the workshop. A use case involving more participants should be investigated to provide more statistically significant results.

6.3. Perspectives

One may use this methodology to explore the possibilities offered by augmented reality instruction adaptation. Building different ARAAS using a common methodology may ease the comparison between studies and thus, help to identify faster the remaining trails available to improve further the operators' performances, working conditions, cognitive resources management and overall user experience. This may improve the acceptability of operators towards augmented reality-based assistance systems and therefore, the deployment of this technology. The comparison of different adaptation strategies should be a focus point for future research as this component of ARAAS remains the least documented. This methodology should also be used to explore the interest and the limitations of using adaptation in maintenance operations' assistance compared to non-adaptive augmented reality systems or simpler digital tools and technologies such as digital checklist.

CRediT authorship contribution statement

Grégoire Mompeu: Conceptualization, Methodology, Software, Writing - Original Draft, Formal analysis, Investigation. **Florence Danglade:** Conceptualization, Methodology, Resources. **Christophe Guillet:** Conceptualization, Resources, Formal analysis. **Frédéric Merienne:** Conceptualization, Methodology, Supervision.

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

Data will be made available on request.

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