Augmenting Human-Machine Teaming Through Industrial AR: Trends and Challenges

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Abstract. Industrial Augmented Reality (AR) is an emerging spatial computing technology which involves the use of head-mounted displays or hand-held devices such as tablets or smartphones to superimpose digital content onto the worker's physical to foster their productivity, learning, and interactions with machines, tools, and other workers. Industrial AR has been adopted in many industries such as manufacturing, healthcare, aerospace, and defense, predominantly for training or remote assistance purposes. Yet, several technical and technological challenges remain to be addressed for industrial AR to evolve from a spatial visualization tool to a more intelligent and adaptive assistive tool that not only augments the spatial and causal reasoning of workers but can also provide them with just-in-time training and support on the job. This chapter provides some technical background on industrial AR and underscores several research and development directions which can potentially materialize this vision.

Keywords: Augmented reality · Collaboration · Assistive technology · Training

1 Introduction

The rapid growth of Artificial Intelligence (AI) and spatial computing technologies such as AR are transforming the landscape of work and human-machine interaction in several industries. These technologies are increasingly adopted by many companies to complement human work and upskill workers [1]. This is also in part due to the shortage of skilled workers, workforce aging and retirement, shifting skill requirements, and the increasing complexity of industrial technology. In manufacturing industry, for example, most companies have predicted a steady demand for workers over the next few years [2], despite shedding nearly 5 million workers between 2000 and 2016 [3], as COVID-19 has increased the need to produce more goods domestically [4]. Yet, about 26% of industrial workers in the United States are retiring [5] and finding skilled workers is more challenging that ever [6]. It is anticipated that near 2.4 million manufacturing jobs will be left unfilled by 2030, which is likely to incur a cost of $2.5 trillion to the U.S. manufacturing GDP [7].

The skills gap in industry is due to the need for complex, career-spanning expertise that are hard to automate in the foreseeable future [8]. Some companies are gradually

C.-Y. Huang and S. W. Yoon (Eds.): ICPR1 2021, ACES 14, pp. 365–385, 2023.
https://doi.org/10.1007/978-3-031-44373-2_22

adopting AR as an experiential training and assistive technology to train and upskill their workers faster [9]. Boeing was one of the early adopters of industrial AR for wire assembly of aircrafts, which led to a 25% reduction in their cycle time and nearly eliminated all the errors that used to occur during the assembly process [10]. Similar early results have been reported by EU-funded STARMATE [11, 12] and SKILLS [13–15] projects, as well as companies such as Honeywell [16], Porsche [17], and Mercedes-Benz [18]. More recent studies also point to the affordances of industrial AR for fostering performance and learning on tasks such as assembly [19–21], maintenance [22, 23], and inspection [24–26].

Extant approaches to industrial AR are mostly concerned around AR authoring [22, 27–31], object tracking and registration [20, 32, 33], comparative analysis of various AR hardware (e.g., headset, tablet, projector, haptic) [19, 25, 34, 35], and remote assistance [36]. The affordances of industrial AR for intelligent, adaptive, and personalized teaming and collaboration between humans and machines are yet to be discovered. Specifically, it is necessary to understand how AR coupled with AI technologies can enhance learning and adaptability of workers on the job through intelligent human-machine teaming, while avoiding potential risks associated with over-dependence on technology and stifled innovation. This chapter first provides a background summary of industrial AR followed by a discussion on the following fundamental research topics and directions for future research and development in this domain.

A. Delivering a given task instruction to a worker through AR can be done in a variety of mode such as text, alert, image, animation, or video. However, each mode is likely to have a different impact on the worker's efficiency, error rate, learning, independence, and cognitive load. It is therefore necessary to explore different modes of instruction delivery through AR and their impact the worker and work. Understanding the usability and limitations of different modes can potentially inform more optimized design of AR user experiences tailored to worker needs and specific task requirements.
B. AR can be used as a training tool prior to task execution or as an assistive tool during task execution. It is important to make such distinction to delineate training scenarios, where AR support is removed after training, from assistive scenarios where AR support is used on a just-in-time basis. Deciding which route to take depends partly on the worker choice complexity [37], novelty and extent of task components, procedures, and functional attributes [38], and the required level of reasoning and decision-making.
C. Learning sciences research underscores the necessity of scaffolding and fading mechanisms that align with the learner's attention and cognitive processes to help them construct knowledge. One-size-fits-all delivery of task information through AR must be replaced with an intelligent system that dynamically scaffolds instructions to the subject matters that workers need information on. Previous research underscores the necessity of devising scaffolding mechanisms that align AR instructions with the learner's attention and cognitive processes to help them construct knowledge [39–41]. Hence, it is necessary to understand the nature of the scaffolding that AR affords, and how to design it in the most effective way for the ongoing success of individual workers through intelligent worker-AR teaming.

D. Extant methods are mainly concerned with the provision of procedural knowledge [42] through AR—the knowledge related to performing sequences of actions. However, this approach merely helps a worker learn "how" to perform a given task without effectively learning the "why" behind work instructions, quality assurance guidelines or specifications, and informal job knowhow. Only by understanding the deeper causal relationships behind the procedural instructions can workers develop the cognitive agility to solve new problems and adapt to new circumstances.

The remainder of this chapter is organized as follows. Section 2 provides a brief overview of the state-of-the-art in industrial AR. Section 3 presents a case study on industrial AR in manufacturing that aims at illuminating research topics A-D. Section 4 discusses several research challenges and research directions within the scope of topics A-D.

2 State-of-the-Art in Industrial AR

A comprehensive review of industrial AR in manufacturing and assembly is provided by [43], which highlights the technical features, characteristics, and industrial applications of AR. The review article categorizes the AR applications in the assembly domain into training, design and planning, and guidance. The main research challenges identified include tracking and registration, collaborative AR interfaces, 3D workspace scene capture, and context-aware knowledge representation. Similar surveys [44, 45] have been conducted on industrial AR applications in maintenance, which emphasize operation-specific applications, AR hardware and development platform comparison, visualization methods, tracking, and authoring solutions. The key technical challenges identified by these articles include automated authoring, context-aware adaptation, and human-AR interactions. Other studies also point to similar challenges in the areas of technology (e.g., tracking/registration, authoring, UI, ergonomics, processing speed), organization (e.g., user acceptance, privacy, cost), and environment (e.g., industry standards for AR, employment protection, external support) [46, 47].

The rest of this section discusses some of the prior work associated with research topics A-D presented in Sect. 1. Topic A seeks to explore the impact of various modes of task instruction delivery through AR on the skill acquisition of workers. Topic A has been addressed by many studies from different angles. For example, a comparison between the effects of verbal, paper-based, and AR instructions on manufacturing workers' productivity, quality, stress, help-seeking behavior, perceived task complexity, effort, and frustration was conducted by [19]. A field study on AR-assisted assembly [48] shows progress in physical and temporal demands, effort, and task completion time. A study on paper-based and head-mounted AR instructions for assembly [49] indicate significant reductions in error rates and task completion times through AR. The effects of an AR fault diagnosis app on the performance of novices with AR support and experts with no AR support were studies by [50]. Results showed that AR-supported novices outperformed experts with no AR support in terms of completion time, accuracy, and cognitive load. The effects of an AR app compared to pictures on inspection task performance were studies by [25], which showed improved task completion time, error rate, gaze shifts, and cognitive load. The effectiveness of different modes of AR information delivery and their measured impact on various task performance metrics on a real-life manufacturing task were recently investigated by the author his team [51], which is reported in Sect. 3.

Topic B presented in Sect. 1 aims at understanding of the affordances of industrial AR as a preliminary training tool versus a just-in-time assistive tool. Many recent studies have partially addressed this topic by investigating the usability, acceptability, and organizational challenges of industrial AR. Field interviews were conducted by [35] to understand the perspectives and acceptance of AR as an assistive tool among assembly workers, which reported generally positive attitude about AR by many workers. A field experiment was also conducted by [52] to study the organizational and technological challenges of industrial AR for industrial workforce training, specifically hardware and software limitations, user acceptance, ergonomics, usability, cost, and integration into shop floor processes. The study concluded that there is a lack of sufficient research on organizational issues, especially on user acceptance and integration. Another study [53] explored the impact of a quiz mode in AR where the user must successfully complete part selection quizzes in addition to AR training prior to task performance. It was shown that the number of errors in new assembly tasks can be reduced by 79% compared to baseline AR training. The usability of AR as an assistive tool for maintenance workers was studied by [54], which reported that a relatively high usability of their AR app compared to traditional modes of instruction. The conditions under which AR can be most effective as an assistive tool versus a training tool are yet to be determined. Section 4 reports some of those conditions based on the findings from a recent study by the author and his team [51].

Topics C and D aim to generate new insights on the potential for AR coupled with AI to enable effective human-technology teaming in industrial workplaces. Extant literature in industrial AR already reports many studies on intelligent context-aware AR apps for industrial applications. A cognition-based interactive AR assembly guidance systems was developed by [33, 55], which leverages tracking and registration techniques for context-aware delivery of task instructions. Another study [56] integrates an intelligent tutoring system comprised of domain knowledge, student models, and pedagogical models into AR for personalized learning. A comprehensive review of research on AI-enabled AR systems was done by [57], which mainly addresses vision system calibration, object tracking and detection, pose estimation, rendering, registration, and virtual object creation in AR. Despite these remarkable efforts, several knowledge gaps related to Topics C and D remain to be addressed. First, learning sciences research underscores the necessity of scaffolding and fading mechanisms [58–61] that align with the learner's attention and cognitive processes to help them construct knowledge [39, 41]. More research is needed on transitioning from "one-size-fits-all" instructions towards personalized and adaptive teaming between workers and industrial machinery through AR. Not addressing this need can lead to overdependence on technology, lack of innovation by workers, and limited industry adoption, among other potential unintended consequences. Second, extant methods are mainly concerned with the provision of procedural knowledge [42] through AR; i.e., the knowledge related to performing sequences of actions. This approach may only help workers learn "how" to perform a given task without effectively learning the "why" behind work instructions, quality assurance guidelines/specifications, and informal shop floor knowledge. Only by understanding the deeper causal relationships behind the procedural instructions can workers develop the cognitive agility to solve new problems and adapt to new circumstances. The remainder of this chapter provides insights into these challenging yet transformative research topics in industrial AR.

3 Case Study: Marine Engine Assembly

This section presents a case study conducted by the author in cooperation with a marine engine manufacturer in Massachusetts and Massachusetts Manufacturing Extension Partnership (MassMEP) to explore some aspects of topics A-D presented in Sect. 1. Details of this study and experimental results are available in [51]. The task involves assembling fuel cell modules of custom-made marine engines, which require following different procedures for each engine model. Traditionally, the task is performed by an experienced assembler who using standard hand/power tools to assemble the fuel cell following instructions provided on a one-page instruction sheet that includes technical drawings and bill of materials (Fig. 1). The main challenge of this manufacturer is that training their novice workers who usually come from mechanic or machinist backgrounds often takes several weeks or months and is done by their experienced workers. This is costly for the manufacturer and often leads to reduced productivity of their existing workers and high scrap or rework rates attributed to their new workers. The core objective of the study was to understand if and how AR can help address this challenge.

3.1 Design of Experiments

Participants. 20 engineering students from Northeastern University participated in the study, including 11 undergraduate students and 9 graduate students, 6 females and 14 males, 4 freshmen, 3 sophomores, 2 juniors, 5 seniors, 5 masters, and one PhD. All participants had an average to high level of familiarity with electro-mechanical assembly using simple tools, and little or no prior experience with AR. A questionnaire was provided to the participants in the beginning to collect their demographics and prior related experiences and use the data to counterbalance the experimental groups. The participants received a brief introduction to the assembly tasks and tools prior to the experiments. They were also briefly trained on using HoloLens 2 (AR headsets) for browsing through the AR app, steps, and different modes of instructions.

Task and Apparatus. The experiments involved electro-mechanical assembly of a fuel cell module for marine engines (Fig. 2, top left), a representative and relatively complex assembly task. The bill of materials contains 26 groups of components that must be assembled over 13 steps using standard tools such as open-ended wrench and Allen socket and rachet. The components were placed on a numbered grid on the worktable in front of the participants (Fig. 2, top right). The participants were divided into two groups of AR-based and paper-based instruction. The AR app was developed using Unity and Mixed Reality Toolkit (Fig. 2, bottom left). The app provides the instructions associated with each step in three different modes (see Fig. 3): (a) expert capture videos with vocal cues generated by mounting a GoPro on the forehead of an expert worker and recording

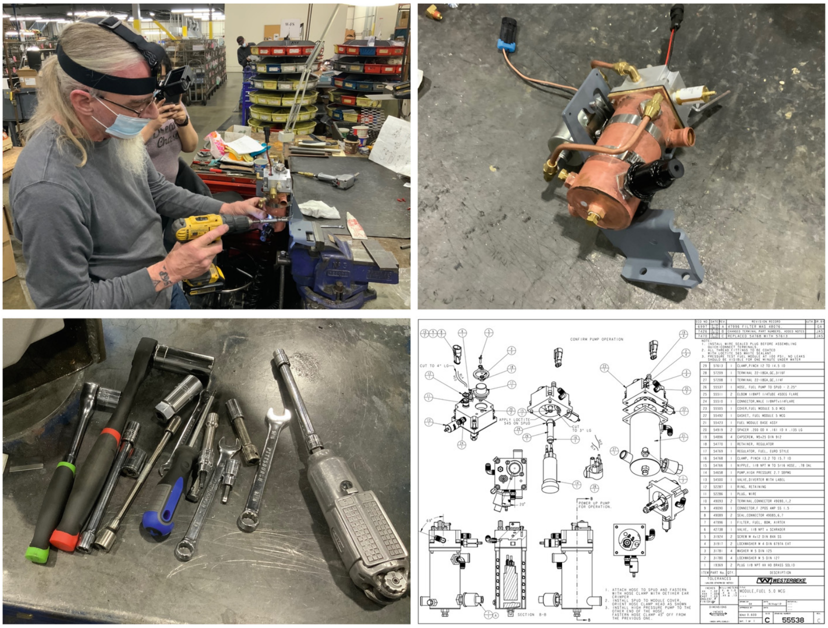

Fig. 1. *Top left*: An expert worker performing the fuel cell assembly task. *Top right*: The fuel cell assembly module. *Bottom left*: Hand and power tools used for assembly. *Bottom right*: Technical drawing and bill of materials.

their task performance (Fig. 2, bottom right), (b) textual descriptions of assembly guides and information for each step (*e.g.*, part numbers, tools, procedures) along with images of the parts to be assembled in that particular step, and (c) interactive 3D CAD animations that allow users to view, rotate, and replay a holographic animation of the assembly step. The AR hardware used for the experiments were HoloLens 2 headsets.

Procedure. A between-subject experiment design was used where the participants were divided into two groups (Fig. 4): Group 1 (AR) and Group 2 (paper). The paper guides include written step-by-step task instructions along with the technical documentation and bill of materials (Fig. 1, bottom right). Each participant performed three assembly cycles on three consecutive days and then returned after a few days to perform a final assembly cycle using the opposite means of instruction (*i.e.*, paper for Group 1 and AR for Group 2). At the end of each round of experiments, both groups of participants filled out a NASA Task Load Index (TLX) questionnaire [62], and the participants who used AR also responded to the following questions:

- In a few words, explain your opinion about the use of AR as a training or assistive tool for manufacturing workers.
- Tell us about your experience with HoloLens (*scale*: very low, low, neutral, high, very high).

  – How do you rate the level of comfort/fit of HoloLens?

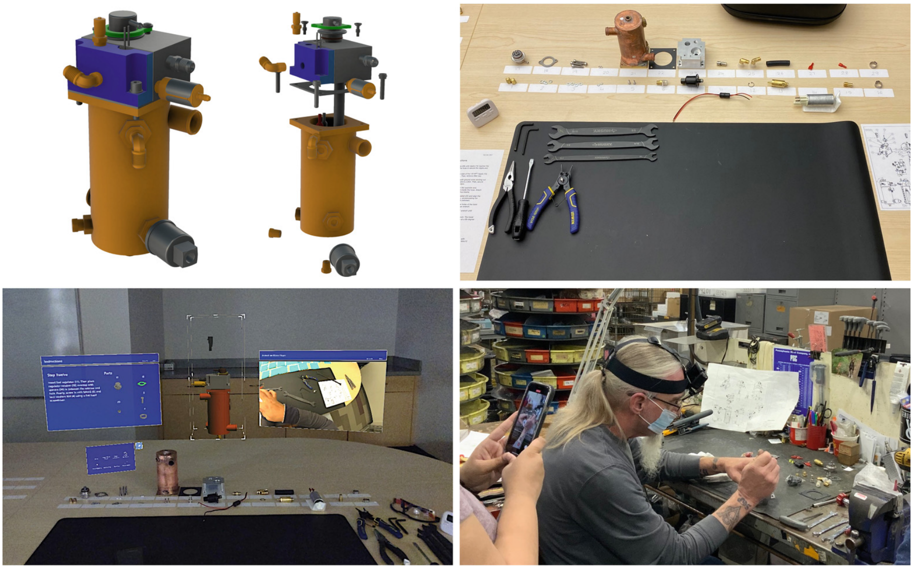

Fig. 2. *Top left:* The assembly part CAD model and exploded view. *Top right*: Worktable setup and tools used for assembly. *Bottom left*: The AR app interface for one assembly step, including textual descriptions and part images, interactive CAD animation, and expert capture video. *Bottom right*: Recording expert capture videos. From [51].

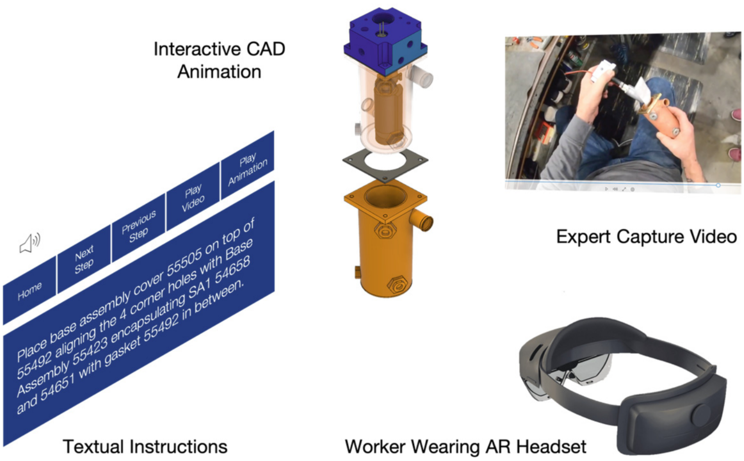

Fig. 3. A schematic of an assembly step instruction in the AR app.

– How satisfied are you with the job you did?
– How do you rate your knowledge of the process to do it without the HoloLens?
– How much do you prefer to learn from a person rather than the HoloLens?
– How distracting or cumbersome do you find HoloLens?

- How do you rate the impact of different modes of AR instructions on your ability to learn the assembly task and improve your performance? (*scale*: not at all, very little, somewhat, quite a bit, a great deal).
  - Text and images
  - Expert capture videos
  - Interactive 3D animations
- In a few words, explain your opinion about the use of AR as a training or assistive tool for manufacturing workers.
- What new, potentially interactive features would you recommend being incorporated in the AR guides?

Fig. 4. *Left*: Participant using AR-based task information (Group 1). *Right*: Participant using paper-based task information (Group 2).

The following data was also collected by observing each individual experiment: round of experiment, mode of guide, time to completion (min), frequency of help-seeking behavior (*i.e.*, number of questions asked during assembly), the types of questions asked (if any), number of errors, and the types of errors made (if any).

Metrics. *Time to completion*: The time needed or taken by the participant to complete the task. It was measured by timing the assembly cycle. *Number of errors*: The number of errors made during each assembly cycle. It was measured by counting the number of errors per cycle and recording the type of error(s) for further analysis. *Help seeking behavior* [19]: The number of times help is requested by the participant per assembly cycle. It was measured by counting the number of times help is requested per cycle and recording the question for further analysis. *Learning curve*: The degree of competence to which the acquired assembly skill is retained through the passage of time. It was measured by recording the amount of improvement in time-to-completion, number of errors, and help seeking behavior over time over temporally separated rounds of experiments on a given task. *Independence from AR*: The ability of AR-trained workers to accomplish the same task without AR, and the impacts of AR on task performance of traditionally trained workers. It was measured by bringing the participants in after a few days to perform the assembly task with the opposite means of task information delivery, record and compare their time-to-completion, number of errors, and help-seeking behavior against their best recorded performance prior to the gap. *Cognitive load*: The amount of working memory used to complete the task following the instructions. It was measured using the NASA-TLX questionnaire. *Utility of different AR modes*: The usefulness of different modes of AR information delivery for learning a task. It was measured using the qualitative questionnaire mentioned above.

Hypotheses. *AR significantly improves (H1) time-to-completion, (H2) number of errors, (H3) help-seeking behavior, (H4) learning curve, (H5) retention, and (H6) cognitive load of workers compared to paper-based instructions.*

3.2 Results

The main results of the experiments are presented in Fig. 5. The key findings of the study were as follows: AR reduces the number of errors by 31–84%. The task completion times of the two groups are about the same; however, that was partly due to the unfamiliarity of participants with AR and some technical issues. Further, most participants reported absolute independence from AR after two/three cycles, which points to the effectiveness of AR in improving task competency, and yet its low utility as an "assistive tool" for routine tasks. Further, several participants suggested devising interactive help and voice command systems.

Time-to-Completion. Statistical analysis of the results of experiments (Fig. 5) indicates a significant difference between the mean time-to-completion achieved by participants in Groups 1 and 2 in Rounds 2 and 3. Group 2 (paper) significantly outperformed Group 1 (AR) in the second and third rounds of experiments in terms of task completion time, even though Group 1 showed a slightly better performance in Round 1. Hypothesis H1 was therefore rejected. It is speculated that Group 2 participants gradually transitioned from following the task information to using their memory to complete the task, while Group 1 participants still went through the AR Instructions. The relatively poor performance of the AR group in terms of completion time was also partly because of their unfamiliarity with the AR headset.

Number of Errors. Statistical analyses on the mean number of errors presented in Fig. 5 show that Group 2 made a significantly higher mean number of errors compared to Group 1 in Round 3 of the experiments. These results are also partly due to a significant reduction in the number of errors made by the participants in Group 1, while the other group maintained an almost steady and relatively higher number of errors throughout Rounds 1–3. With these findings, hypothesis H2 can be accepted, which indicates the significant impact of spatiotemporal alignment of task information and visual/vocal cues with experience on the number of errors made during task performance.

Help-Seeking Behavior. Only two participants from each group sought help related to AR app, part orientation, and sequence of assembly. This observation was consistent

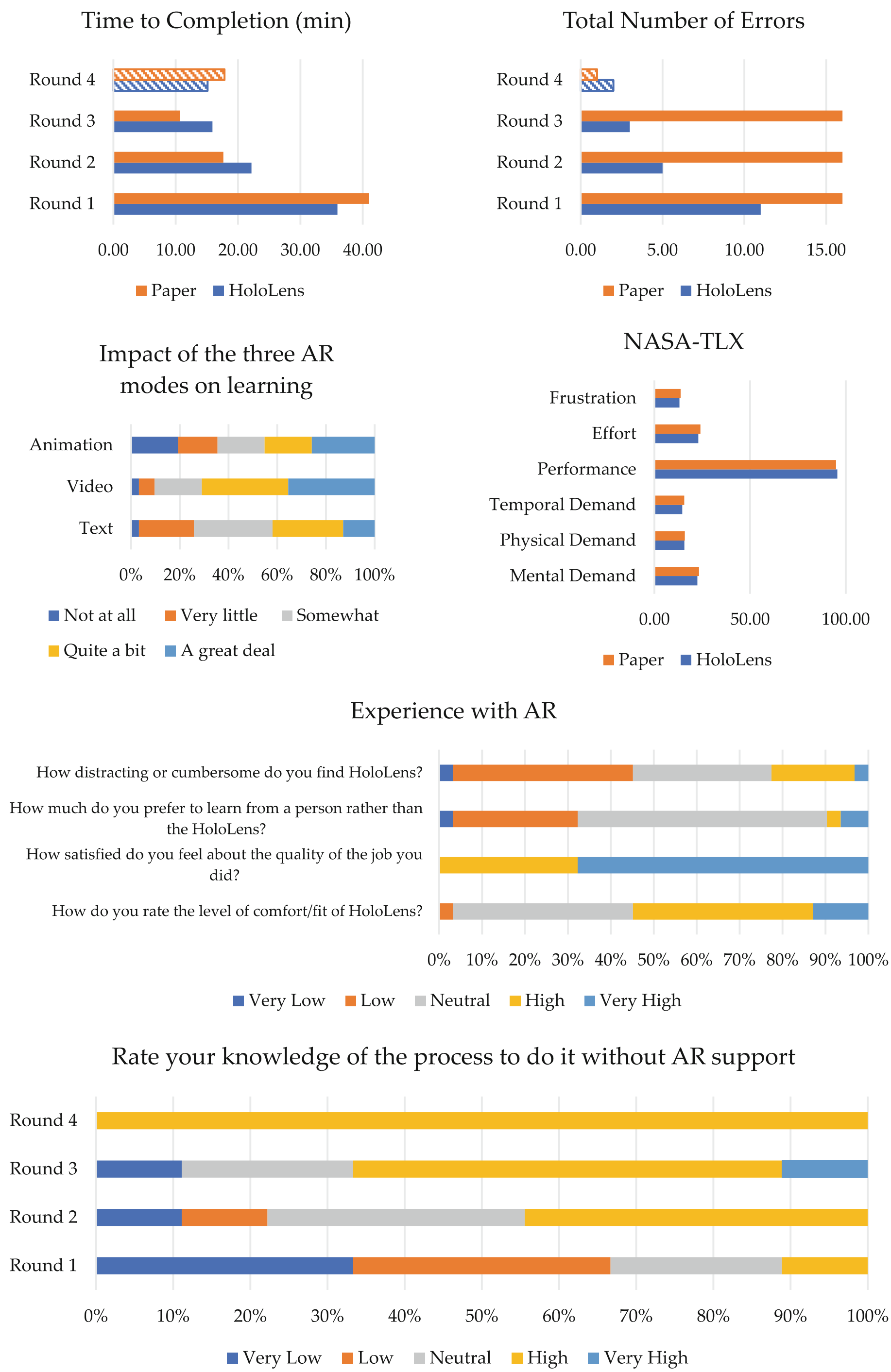

Fig. 5. Results of the human subject experiments.

with the comments made by the plant manager of the marine engine manufacturer that workers often tend to overthink and not reach out for help due to fear of embarrassment or overconfidence, which may lead to failures down the line. This is yet another motivation to create AR training and assistance systems that can address the needs and struggles of workers without them having to reach out (or not reach out due to the feelings or fear or embarrassment) to their coworkers or supervisors for help. These findings reject hypothesis H3.

Learning Curve. Statistical analyses on the differences between mean time-to-completion and mean number of errors of each group between Rounds 1 and 2, Rounds 2 and 3, and Rounds 1 and 3 indicated significant reductions in mean time-to-completion between each round for both groups. It can therefore be stated that the means of instruction (*i.e.*, paper versus AR) does not have any noticeable impact on task completion time. However, observations also showed that although Group 2 made no improvement in the number of errors made during assembly, Group 1 participants were able to significantly reduce the number of errors between Rounds 1 and 3. It is thus concluded that not only the use of AR leads to fewer errors, but it also helps workers significantly reduce the number of errors in subsequent rounds of operation. Hypothesis H4 is therefore accepted.

Independence from AR. The mean time-to-completion of each group in Round 3 and Round 4 (see Fig. 5) comprised two interesting observations. First, Group 1 who switched from AR guides in Round 3 to paper guides in Round 4 could complete their task even slightly faster in Round 4 than in Round 3. Here is a quote from a Group 1 participant after completing Round 4: "*It was less cumbersome to assemble the components without the AR headset on, but the paper drawings were much harder to interpret. I much prefer the CAD animations; I imagine if I were to have started first with the paper-based instructions and drawings, it would have taken me much longer to complete the task initially. I suspect the only reason it took me around the same time to complete the task with paper-based instructions is simply because I had assembled the component three times already.*" Second, Group 2 demonstrated significantly longer completion times in Round 4 using AR than in Round 3 using paper, which is to some extent due to their lack of prior experience with AR app. Moreover, Group 1 maintained their relatively lower mean number of errors in Round 4 even after a few days, while the mean number of errors by Group 2 was significantly reduced in Round 4. This indicates the role of AR in accelerating workers' learning and competency, its usefulness for traditionally trained workers in avoiding more errors during task performance, and better memory retention than paper-based instructions which results in a significantly lower number of errors even after AR support is removed. Hypothesis H5 was therefore accepted.

Cognitive Load. Results of the NASA-TLX questionnaire (Fig. 5) indicate almost identical levels of mental demand, physical demand, temporal demand, perceived performance, effort, and frustration for both groups. These observations therefore reject hypothesis H6. The assembly task was perceived as not too challenging by most participants.

Modes of Instruction Delivery. The collected responses to the questions about the impacts of different modes of AR (*i.e.*, text, 3D animation, video) on task performance, independence from AR, and experience with AR varied among the participants. Some found text instructions and 3D CAD animations more helpful: *"The text instructions and CAD animation together provided a great deal of detail about how to complete the current step. Reading the instructions and visualizing the task through the animation provided clarity on how to complete the task and what the subassembly should look like afterward. Although helpful, the video was not completely necessary, and I skipped it for most of the steps." "Being able to rotate and view the CAD model was super helpful during assembly. It allowed me to easily understand how all the parts fit together. The other two were useful, but tended to get in the way as I was putting physical pieces together."* Some other participants, however, found videos with vocal cues along with textual instructions more helpful: *"The CAD animation was somewhat useful, but I preferred the video, as the instructor assembled the part at about the same speed that I was. Additionally, there were little comments that helped, which a silent CAD animation didn't include." "I tended to listen to the verbal cues from the video, occasionally checking the text to confirm part numbers, and only once or twice double-checking with the CAD animation."*

Independence from AR. Group 1 were initially highly dependent on AR: 70% of the participants reported high or very high dependence on AR. This dependency, however, gradually declined as only 20% of Group 1 were highly or very highly dependent on AR by the end of Round 3. On the contrary, 90% of the participants from Group 2, who switched from paper to AR in Round 4, stated that they are highly independent from AR. Nevertheless, switching to AR helped this group significantly reduce the number of errors made during assembly. Moreover, only 10% of the participants expressed a preference to be trained by a person rather than by the AR app. These number are expected to vary for actual manufacturing workers who belong to different age groups and educational levels/backgrounds.

AR for Just-In-Time Assistance. The participants were asked to comment on the use of AR as an assistive tool for workers. Text-to-speech features were recommended to read out the textual instructions. Some also suggested the use of voice commands for hands-free interaction with the AR content. Menu-based, non-procedural provision of task information were suggested by some participants so the user can call certain instructions on demand, rather than having to go through a fixed sequence of steps. It was suggested to include more interactive and personalizable layout design for the AR app so the user can use the layout they feel most comfortable in. Some participants suggested help options that allow the user can get assistance when something goes wrong or if they have a question about the task.

4 Discussion: Towards Intelligent AR Systems

Industrial AR has the potential to transform workplace-based learning for future workers and thus bridge the labor market mismatch and enhance the productivity and/or quality of future work. Yet, the technology is still evolving, and several key challenges associated with technology development, socioeconomic impacts, and human factors are yet to be addressed. The following section discusses several directions in line with research topics A-D discussed in Sect. 1 with the vision of turning AR into an intelligent, adaptive, and personalized assistant for incumbent and new workers across different industries.

State-of-the-art industrial AR systems still offer limited personalized interactions between workers and AR, and primarily offer procedural, one-size-fits-all instructions with minimal attention to the individual worker's needs and knowledge. This may lead to potential unintended consequences such as overdependence on technology and stifled innovation [13, 15, 63], and also hinder industry adoption. The provision of procedural knowledge [42] through AR—the knowledge related to performing sequences of actions—merely helps workers learn "how" to perform a given task without effectively learning the "why" behind work instructions. That prevents workers from developing a deep understanding of the underlying causal relationships behind the procedural instructions can workers develop the cognitive agility to solve new problems and adapt to new circumstances, especially in tasks that involve complex reasoning and decision-making. Future research must explore how AR can intelligently tailor scaffolds to the specific needs of workers to enhance not only their performance efficiency but their complex reasoning skills for solving novel problems and adapting to changing work environments. It is therefore critical to build new methods at the nexus of AI, AR, and human-machine interaction to understand how various sources of multimodal data captured by AR devices, industrial machinery, and any other smart device or sensor can be harnessed to interpret, predict, and guide the behavior of industrial workers and enable intuitive human-machine teaming.

Future research must build new inference engines into AR for interactive and personalized task assistance informed by multimodal context data, user intent, and multidimensional digital data. The outputs of the inference engine can be generated either automatically or in response to user inputs (*e.g.*, buttons, menus, dialog, hand gestures, gaze). The automated outputs can be more focused on critical task information (*e.g.*, safety features, warnings) while the on-demand outputs may involve declarative knowledge or task assistance. Such inference engines can progressively tailor the instructions to the specific needs of users based on the collected data on their performance. That is, they can capture data on the history of user interactions with the auto-generated content (e.g., interactions with menus, questions asked, or "gaze-time") for each content, and gradually remove contents below a certain usage threshold. A set of logical rules can be applied for the inference engine to generate proper automated or on-demand system outputs in any of the following or similar forms (Fig. 6):

- **Spatially registered 3D visualizations.** Given the identified 6D poses of objects, AR systems can superimpose task guidance and digital information on physical objects (*e.g.*, part, robot, controller), along with textual instructions, and visualizations to boost the spatial reasoning abilities of users.
- **Notifications.** Considering user intent and task status, AR systems can generate visual or auditory notifications, based on job sheets and operations manuals, to ensure the user is aware of important safety and operational features.
- **Recommendations.** AR systems can leverage multidimensional digital data (*e.g.*, GD&T, 3D annotations, material specifications, and process notes) to assist workers with reasoning about observed task progression.
- **Spatial/causal reasoning animations.** AR systems can include detailed 3D animations of the process for users to visualize what cannot be seen during operation.

- **Expert capture videos.** AR systems. Can provide users with audiovisual "expert stories", captured using GoPro or over-the-shoulder cameras, which can be activated using voice command, menus/buttons, or hand gestures on demand.
- **Remote assistance.** AR systems can also allow users to video call remote experts from the app and share their screen to get immediate assistance.

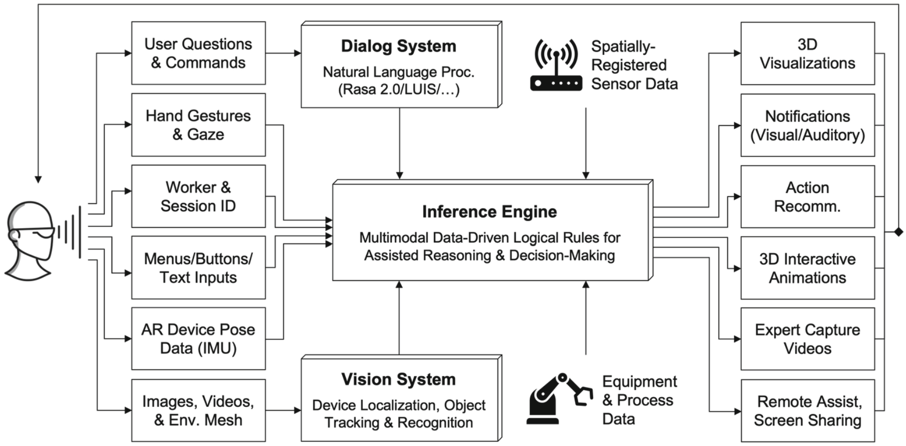

Fig. 6. Schematic of an intelligent AR system with an inference engine for context-aware human-machine teaming in industrial settings.

Consider, for example, human-robot collaboration in industry where workers and collaborative robots synchronously process the same task in a shared physical workspace. This is an increasingly common scenario in many industrial settings such as factories, warehouses, and distribution centers, especially given the fact that human-robot teaming is known to reduce idle time by 85% compared to when the task is performed by all human teams [64]. Yet, the integration of collaborative robots into factories is currently limited to structured operations with known, minimal, and fully predictable interactions with humans. That is, collaborative robots are currently being used in factories as an advanced, automated tool rather than an active and intelligent coworker for the human operator. This "black-and-white" approach to automation in factories has reached its limits, because many manufacturing tasks such as machine tending, assembly, inspection, and part transfer are not 100% repetitive and involve many variations that cannot be handled by exiting robots or require time-consuming reprogramming. This makes today's robotic coworkers inadequate assistants to human workers and impedes human-robot teamwork.

AR coupled with AI capabilities can bridge this gap by functioning as a mediator to enable the worker to preview and modify the programs and policies taught to the robot, which will in turn lead to the progressive adaptation and convergence of shared mental models between them (Fig. 7). AR can also facilitate the communication of the worker's intent to the robot through both explicit (*e.g.*, hand gestures, gaze) and implicit (*e.g.*, eye/head gaze, wearables) modes of interaction. AR can also enhance robot-to-worker interaction through multimodal communication channels such as 3D visualization, haptics, and/or auditory signals. Such an intelligent AR mediator system can potentially advance the understanding of how transparent sharing of intent and awareness can shape teamwork fluency and trust between workers and robots.

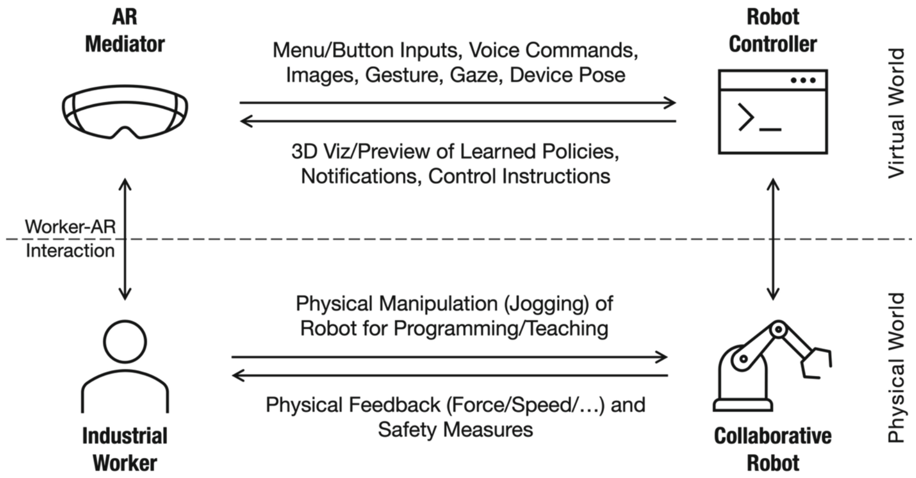

Fig. 7. Two-way communication of information and intent between workers and robots through an intelligent AR mediator.

5 Conclusions

The newer wave of industrial automation is not so much to replace workers but rather to increase precision, safety, and product quality [65]. Modern automation is about continuing to automate tasks that are dirty, dull, and dangerous, but preserving the ones that are "value-added" and often desirable parts of the jobs for human workers. Those kinds of value-added jobs are specifically the ones that are hard to automate, either because they require sophisticated and precise manipulation of physical objects that only a human is capable of or because they require complex reasoning and decision-making that machines are not capable of. Informed by the experiments and conceptual frameworks presented in Sects. 3 and 4, respectively, the author and his team assembled a panel of ten experts from major industrial, academia, and federal institutions in the U.S. and Europe to further illuminate the potentials and risks of industrial AR in the human-centered automation era.

The discussions were facilitated by four high-level questions. (1) How widespread do you think the adoption of AR technology in manufacturing will be in the next 5 years? Which firms would be best suited to adopt such technologies (*e.g.*, size, product type, capital/labor mix)? What impact might the adoption of AR technologies have on the skill requirements for specific job roles in assembly? To what degree can AR technologies be used to train the future manufacturing workforce? (2) What are the potential benefits and risks of AR for workplace-based learning on complex, career-spanning expertise in areas such as assembly and maintenance? Do you see other training techniques/technology alternatives on the horizon? (3) There is some evidence that overreliance of workers on AR can cause "brittleness" of knowledge [63], hinder learning, and deteriorate performance in adapting to novel situations. In your opinion, what are the impacts of AR on the ability of workers to learn new tasks in a way that enhances their flexibility in transferring their knowledge to new situations? (4) How can we interpret, predict, and guide the behavior of AR-supported assembly workers through adaptive scaffolding of instructions to the expertise level of individual workers, and immediate AR-based feedback on their actions and decisions? What are the implications for the design of future AR technologies?

This chapter is concluded by presenting seven key insights drawn from the panel discussion about the challenges and future trends in industrial AR:

1. AR can potentially be a disruptive assistive technology for manufacturing tasks that are not rote and require complex reasoning and decision-making; for example, inspection in regulated industries such as aerospace.
2. The acceptability of AR as a "tool" is likely to differ among incumbent and future workers and different demographics. The experiments presented in this paper only featured young and educated engineering students. Current AR technology may not be well received by more senior workers because the interfaces are not as intuitive as they should be for someone with little or no experience with AR or even with computers.
3. AR can increase the accessibility of manufacturing jobs to workers with different demographic characteristics by allowing for self-guided learning without the need for physical and real-time interaction with a trainer.
4. AR can create new opportunities for remote learning and assistance from larger, and possibly more diverse, pools of physically/temporally distant coworkers. It can also enable remote assistance and collaboration by allowing the on-site worker to share their experience with a remote expert and get immediate feedback with 3D visual cues.
5. The adoption of AR by companies will require rigorous justification through both proof-of-concept and economic cost-benefit analyses. It is important to educate companies on the potential impacts of AR on efficiency and productivity, the skills required for building, maintaining, and updating the content, the costs of software and hardware, and the acceptability of the technology among both incumbent and entry-level workforce.
6. Scalability must be regarded as a key criterion for the ideation and design of AR technologies. The marine engine manufacturer studied, for example, makes tens or hundreds of different variations of a given part family.
7. AR can be coupled with digital thread technologies to provide workers with part, process, and task information such as geometric dimensions and tolerances (GD&T), 3D annotations, material specifications, and process notes [66, 67] in real-time. AR can also leverage industrial Internet-of-Things (IoT) data to enable access to real-time machine data in semiautomated tasks such as robotic assembly or CNC machining.

Acknowledgement. This material is based upon work supported by the National Science Foundation under the Future of Work at the Human-Technology Frontier Grant No. 2128743. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. I acknowledge the support of our expert panel and industry partners.

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