Advanced Engineering Informatics 50 (2021) 101410

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Exploring augmented reality for worker assistance versus training

Mohsen Moghaddam [a,*], Nicholas C. Wilson [b], Alicia Sasser Modestino [c], Kemi Jona [d], Stacy C. Marsella [e]

[a] Department of Mechanical and Industrial Engineering, Northeastern University, Boston, MA 02115, USA
[b] Center for Advancing Teaching and Learning Through Research, Northeastern University, Boston, MA 02115, USA
[c] College of Social Science and Humanities, Center for Health Policy and Healthcare Research, Northeastern University, Boston, MA 02115, USA
[d] Experiential Digital Global Education Group, Northeastern University, Boston, MA 02115, USA
[e] Khoury College of Computer Sciences, Northeastern University, Boston, MA 02115, USA

ARTICLE INFO

Keywords:
Augmented reality
Electro-mechanical assembly
Workforce training
Workplace-based learning

ABSTRACT

This paper aims at advancing the fundamental understanding of the affordances of Augmented Reality (AR) as a workplace-based learning and training technology in supporting manual or semi-automated manufacturing tasks that involve both complex manipulation and reasoning. Between-subject laboratory experiments involving 20 participants are conducted on a real-life electro-mechanical assembly task to investigate the impacts of various modes of information delivery through AR compared to traditional training methods on task efficiency, number of errors, learning, independence, and cognitive load. The AR application is developed in Unity and deployed on HoloLens 2 headsets. Interviews with experts from industry and academia are also conducted to create new insights into the affordances of AR as a training versus assistive tool for manufacturing workers, as well as the need for intelligent mechanisms that enable adaptive and personalized interactions between workers and AR. The findings indicate that despite comparable performance between the AR and control groups in terms of task completion time, learning curve, and independence from instructions, AR dramatically decreases the number of errors compared to traditional instruction, which is sustained after the AR support is removed. Several insights drawn from the experiments and expert interviews are discussed to inform the design of future AR technologies for both training and assisting incumbent and future manufacturing workers on complex manipulation and reasoning tasks.

1. Introduction

The future of manufacturing workforce faces a “perfect storm” of challenges: A shortage of skilled workers due to workforce aging and retirement, shifting skill requirements due to the introduction of AI, automation, and other advanced technologies, and a lack of understanding and appeal of manufacturing jobs among younger cohorts. Despite shedding nearly 5 million workers between 2000 and 2016 [1], most manufacturing companies have predicted that the demand for workers will remain the same or even increase over the next few years [2] as the COVID-19 pandemic has exposed the need to produce more goods domestically [3]. At the same time, manufacturers anticipate that few of the remaining jobs will be easily automated in the near future. Instead, technology is now being used to complement human work and upskill workers [4]. Yet, nearly 26% of manufacturing workers in the United States are 55 and older [5], and manufacturers have cited difficulties in finding skilled workers to fill jobs for the past decade [6]. Consequently, 2.4 million manufacturing jobs are anticipated to be left unfilled by 2030 with a projected cost of $2.5 trillion to the U.S. manufacturing GDP [7].

The increasing adoption of new technologies is also likely to present a potential mismatch as manufacturers will increasingly demand that incumbent workers develop the ability to work with new technology on the job while also raising skill requirements for new entry level workers [8]. The skills gap in manufacturing is driven by the need for complex, career-spanning expertise in areas such as assembly, maintenance, and inspection [9]. Augmented Reality (AR) has been recently adopted as a novel experiential training technology for faster training and upskilling of manufacturing workers on complex tasks with the potential to reduce new hire training time by 50% [10]. An early adopter of AR for wire

* Corresponding author.
E-mail addresses: m.moghaddam@northeastern.edu (M. Moghaddam), 3ni.wilson@northeastern.edu (N.C. Wilson), a.modestino@northeastern.edu (A.S. Modestino), k.jona@northeastern.edu (K. Jona), s.marsella@northeastern.edu (S.C. Marsella).

https://doi.org/10.1016/j.aei.2021.101410
Received 29 April 2021; Received in revised form 22 July 2021; Accepted 31 August 2021
Available online 9 September 2021
1474-0346/© 2021 Elsevier Ltd. All rights reserved.

assembly of aircrafts, Boeing reported a 25% reduction in cycle time and a near-zero error rate [11]. Studies by the European projects STARMATE [12,13] and SKILLS [14–16], and by companies such as Honeywell [17], Porsche [18], and Mercedes-Benz [19] also reported up to 50% improvement in production time with over 80% reduction in error rates using AR. Subsequent studies proved the effectiveness of AR technology in improving task performance and training time on various manufacturing tasks such as assembly [20–22], maintenance [23,24], and inspection [25–27].

The state-of-the-art in industrial AR is predominantly focused on AR content creation and authoring solutions [23,28–32], improving object tracking and registration [21,33,34], studying the effectiveness of various modes of AR (*e.g.*, head-mounted, hand-held, projector, haptic) [20,26,35,36], and studying the applications of AR for remote assistance [37] (see Section 2 for details). Yet, several fundamental questions remain in regard to the best modes of task information delivery through AR, task-specific effectiveness of AR versus traditional assistance/training mediums, and the potentials and pitfalls of turning AR technology into an intelligent assistive tool for industrial workers. This paper aims at advancing the fundamental understanding of the affordances of AR as a disruptive workplace-based learning and training technology to support future and incumbent manufacturing workers in performing manual or semi-automated tasks that involve both complex manipulation and reasoning. Specifically, the paper contributes new insights into three fundamental questions:

11. *What is the most effective way of delivering various task information to the worker? What are their impacts on their efficiency, number of errors, learning, independence, and cognitive load?* These questions aim at exploring the effectiveness of different modes of task information delivery through AR (*e.g.*, text, images, 3D animations, expert capture videos), and how they impact the ability of workers to complete the task faster and fewer errors, and the transition from novice to expert. Insights about the usability and limitations of different modes of AR information can be informative for designing and prototyping user-centered AR applications that best meet the needs of workers.
21. *What are the affordances of AR as a training tool prior to task performance* versus *as an assistive tool during task performance?* This question is motivated by the importance of delineating training applications where AR support is removed after a while from assistive applications where AR hardware and apps are used as permanent tools on demand. It is argued that the decision between these two applications depends upon the worker choice complexity [38], the novelty of components, procedures, and functional attributes associated with a given task [39], and the expected complexity of the reasoning and decision-making elements of the task. Identifying the right application is a key prerequisite for informing the design of industrial AR technologies and facilitating industry adoption.
31. *How can future AR technologies transition from passive delivery of task information to intelligent and proactive teaming with the worker?* One-size-fits-all delivery of task information via AR must be replaced with an intelligent system that dynamically scaffolds instructions to the subject matters that individual 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 [40–42]. It is therefore critical 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.

This paper presents the results of a case study along with industry research to advance the fundamental understanding of Q1-Q3 and proposes several research directions for future design and development of AR technologies for workplace-based learning in manufacturing. Section 2 provides details of the design of the laboratory experiments and expert interviews in detail. Section 3 presents the experimental results and analyses. Informed by the experiments and expert interviews, Section 4 discusses several research challenges and directions associated with Q1-Q3.

2. Related work

Several comprehensive review articles have been published in recent years discussing the state-of-the-art, trends, and challenges of industrial AR research practice. Wang et al. [43] provide a comprehensive review of AR-based assembly systems, their technical features, characteristics, and industrial applications. They categorize the applications of AR in assembly into assembly training, assembly design and planning, and assembly guidance, and identify four research challenges and future trends in this area: tracking and registration, collaborative/shared AR interfaces, 3D workspace scene capture, and context-aware knowledge representation. Fernandez del Amo et al. [44] and Palmarini et al. [45] conduct systematic reviews of scientific articles on industrial AR for maintenance with emphasis on application areas, maintenance operations, AR hardware, development platform, holographic visualization methods, tracking, and authoring solutions. Their findings point to the methods for content creation/authoring, context-aware content adaptation, and the analysis of user interactions with AR as the main areas of research in industrial AR with special reference to maintenance applications. Masood and Egger [46] and Egger and Masood [47] present a detailed review on the state of AR research in Industry 4.0 and intelligent manufacturing, and summarize the research challenges in three categories 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).

This work is motivated by three fundamental questions that remain at least partially unanswered by the extant industrial AR literature summarized in [43–47]. The first question seeks to understand the impact of various modes of task information delivery via AR on the skill acquisition of industrial workers. Q1: *What is the most effective way of delivering various task information to the worker? What are their impacts on their efficiency, number of errors, learning, independence, and cognitive load?* Several studies have addressed this issue from a variety of perspectives, some of which are discussed here as examples. Vanneste et al. [20] compare the effects of verbal, paper-based, and AR instructions on the performance of assembly workers in terms of productivity, quality, stress, help-seeking behavior, perceived task complexity, effort, and frustration. A field study on AR-assisted assembly by Koumaditis et al. [48] indicates improvements in physical and temporal demands, effort, and task completion time. A comparative study between paper-based and head-mounted AR instructions by Werrlich et al. [49] reports significant improvements in error rates along with longer task completion times in assembly tasks using AR. Smith et al. [50] study the effects of a mobile AR fault diagnosis app on the performance of novices compared to a group of experts with no AR support, and report significantly better performance by AR-supported novices in terms of task time, accuracy, and cognitive load. Polvi et al. [26] compare the effects of an AR app versus pictures on inspection task performance and report significant improvements by AR in task completion time, error rate, gaze shifts, and cognitive load. *Knowledge gap*: The effectiveness of different modes of AR information delivery and their measured impact on various task performance metrics on a real-life manufacturing task remain to be explored.

The second question posed by the authors strives to advance the understanding of the affordances of AR technology as a preliminary training tool versus a permanent assistive tool. Q2: *What are the affordances of AR as a training tool prior to task performance* versus *as an assistive tool during task performance?* This question is motivated by the limitations of current AR software and hardware technology, which may hinder the use of AR as a permanent assistive tool. This issue has been explored by a number of recent studies on the usability, acceptability, and organizational challenges of industrial AR. Danielson et al. [36] perform field interviews to understand the operators' perspectives and acceptance of AR as an assistive tool for engine assembly and report a generally positive sentiment about AR by most industrial workers. Masood and Egger [51] conduct a field experiment to investigate the organizational and technological challenges of industrial AR for assembly training, specifically hardware/software limitations, user acceptance, ergonomics, usability, cost, and integration into shop floor processes. Results of their experiments and surveys point to a lack of sufficient research on organizational issues, especially on user acceptance and integration. Werrlich et al. [52] study 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. Their findings show a 79% reduction in the number of errors in new assembly tasks compared to baseline AR training. Brice et al. [53] study the usability of AR as an assistive tool for industrial maintenance workers and report a minimal effect on task completion time and high usability of their custom AR application compared to traditional modes of instruction. *Knowledge gap*: It remains unclear under what conditions AR can be most effective as an assistive tool versus a training tool, and how to systematically identify and overcome barriers to industry adoption.

The final question aims to create new insights on the potential for AR coupled with other spatial computing methods to enable effective human-technology teaming in industrial settings. Q3: *How can future AR technologies transition from passive delivery of task information to intelligent and proactive teaming with the worker?* Several researchers have developed and tested intelligent context-aware AR apps for a variety of manufacturing tasks such as assembly, maintenance, and inspection. For example, Wang et al. [34,54] develop cognition-based interactive AR assembly guidance systems which leverages advanced tracking and registration methods for context-aware delivery of task information. Westerfield et al. [55] integrate an intelligent tutoring system comprising domain knowledge, student models, and pedagogical models into AR to provide a personalized learning experience to each individual learner. Sahu et al. [56] present a comprehensive review of research on AI-powered AR systems, which is predominantly focused on vision system calibration, object tracking and detection, pose estimation, rendering, registration, and virtual object creation in AR. *Knowledge gaps*: (1) Learning sciences research underscores the necessity of scaffolding and fading mechanisms [57–60] that align with the learner's attention and cognitive processes to help them construct knowledge [40,42]. However, more research is needed on transitioning from one-size-fits-all instructions with minimal attention to individual worker's needs and knowledge towards personalized interactions between workers and AR systems. A lack of such personalization may lead to potential unintended consequences, such as overdependence on technology and stifled innovation, and hinder industry adoption. (2) Extant methods are mainly concerned with the provision of procedural knowledge [61] through AR—the knowledge related to performing sequences of actions. Yet, 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. This study aims to provide preliminary insights into these challenging and potentially transformative research topics in industrial AR.

3. Materials and methods

Laboratory experiments were conducted in collaboration with a marine engine manufacturer in Massachusetts to investigate the impacts of AR on task performance. Furthermore, interviews were conducted with experts from industry and academia to create insights into the affordances of AR as a training versus assistive tool for manufacturing workers (Q2) as well as the need for intelligent mechanisms that enable adaptive and personalized interactions between manufacturing workers and AR (Q3). The research methodology is inspired by [20] and designed based on the multidisciplinary expertise of the authors and their experience in experimental design. The study was approved by the Institutional Review Board of Northeastern University (IRB# 20-06-21).

3.1. Laboratory experiments

Participants. The study participants were 20 engineering students at Northeastern University, 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 no or minor 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. 1-a), a representative and relatively complex assembly task recommended by the authors' industry partners. The subassembly part consists of 26 groups of components which have to 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. 1-b). Two means of instruction were available: AR and paper-based instruction. The AR app was developed in Unity using the Mixed Reality Toolkit. The app includes three modes of delivering the assembly guides and information to the subjects (Fig. 1-c): (1) expert capture videos with vocal cues, which were generated by mounting a GoPro on the forehead of an expert worker and recording their task performance (Fig. 1-d), (2) 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 (3) 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. 2): Group 1 (AR) and Group 2 (paper). The paper guides include written step-by-step task instructions (same as the textual instruction on the AR app) along with a 2D CAD drawing with orthographic and exploded views of the part with component numbers (Fig. 2-c). Each participant performed three assembly cycles on separate dates using their designated mode of instruction (*i.e.*, AR for Group 1 and paper for Group 2) 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). The reason behind the proposed design of experiments is to measure the independence of Group 1 from AR as well as the usefulness and acceptability of AR for Group 2, with the assumption that the first three rounds of experiments were sufficient for training both groups of participants on the assembly task. The experiments were conducted with two participants in the lab at a time with a partition in-between to avoid possible COVID-19 transmission. At the end of each round of experiments, both groups of participants filled out a NASA-TLX (Task Load Index) questionnaire [62], and the participants who used AR also responded to the following questions:

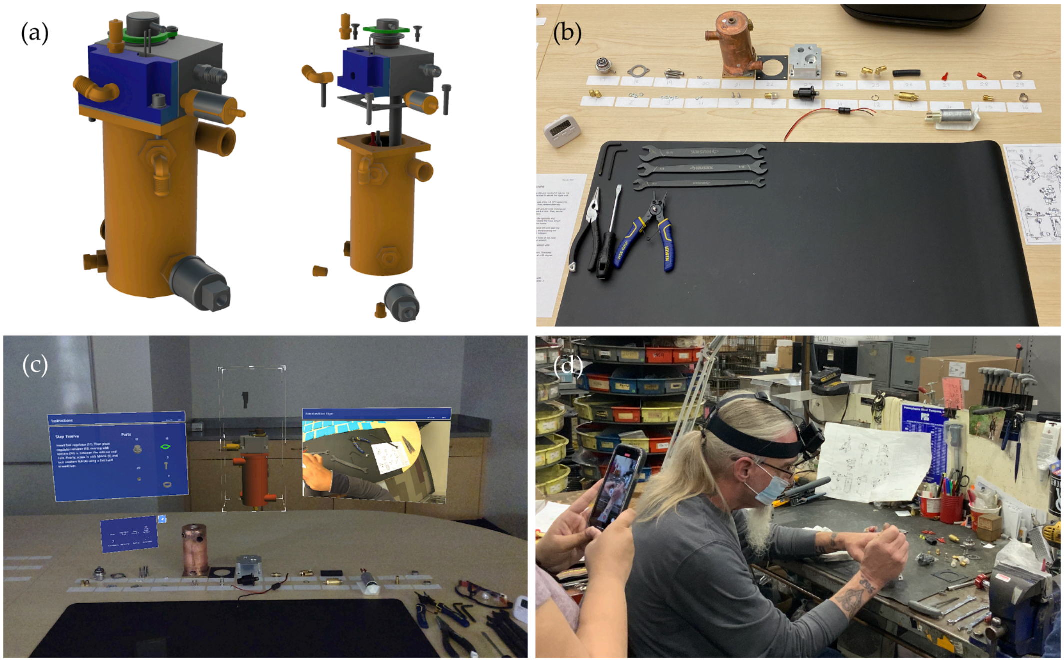

Fig. 1. (a) The assembly part CAD model and exploded view. (b) Worktable setup and tools used for assembly. (c) The AR app interface for one assembly step, including textual descriptions and part images, interactive CAD animation, and expert capture video. (d) Recording expert capture videos.

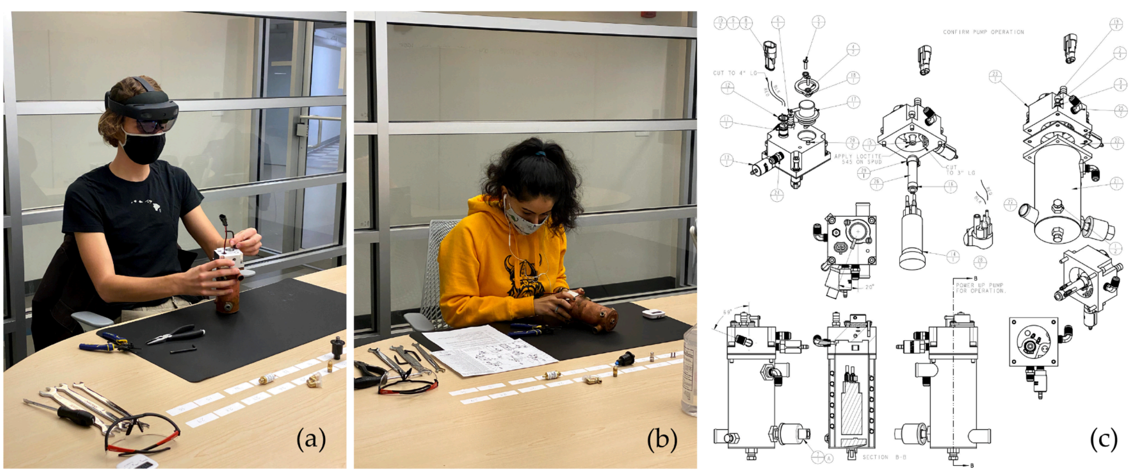

Fig. 2. (a) Participant using AR-based task information. (b) Participant using paper-based task information. (c) 2D CAD drawings provided to the participants that used paper-based task information.

- 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?
  - 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?

In addition to the above questionnaire, the experimenters also collected the following data from 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. The following metrics were used to measure the task performance and learning of the study participants.

- *Time to completion*: The time needed or taken by the participant to complete the task. *Measurement*: Time the assembly cycle.

- *Number of errors*: The number of errors made during each assembly cycle. *Measurement*: Count the number of errors per cycle and record the type of error(s) for further analysis.
- *Help seeking behavior* [20]: The number of times help is requested by the participant per assembly cycle. *Measurement*: Count the number of times help is requested per cycle and record the question for further analysis.
- *Learning curve*: The degree of competence to which the acquired assembly skill is retained through the passage of time. *Measurement*: Measure 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. *Measurement*: Bring 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. *Measurement*: NASA-TLX questionnaire.
- *Utility of different AR modes*: The usefulness of different modes of AR information delivery for learning a task. *Measurement*: Questionnaire.

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. Two-sample t-test is utilized to test H1, H2, H3, and H6, i.e., the statistical significance of the differences between the means of Groups 1 and 2. Paired t-test is utilized to test H4 and H5, i.e., to compare the performance of participants to self between rounds 1–2 and rounds 2–3 to measure learning (i.e., H4) and between rounds 3–4 to measure retention (i.e., H5).

3.2. Expert interviews

A group of 10 experts from industry, research institutions, and community colleges was assembled to discuss the potentials, anticipated benefits, risks, and barriers to adoption of AR for training and workplace-based learning. The anonymized roles and affiliations of the experts are as follows:

- Director of a non-profit association of small to medium-sized manufacturers, USA
- Dean of science and engineering at a community college, USA
- Scientific advisor at the engineering division of a government agency, USA
- Professor of advanced manufacturing at a community college, USA
- Professor of business and management at a major research institute, USA
- Professor of production engineering and automation at a major research institute, Europe
- Professor of practice in advanced manufacturing at a major research institute, USA
- Technology development manager at a major industrial automation company, Europe
- Manufacturing engineer at a major aerospace company, USA
- Director at a major digital technologies company, USA

The discussions were guided by four high-level, open-ended 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?

4. Results

This section presents and analyzes the results of the laboratory experiments followed by a summary of insights drawn from the expert interviews.

4.1. Task performance

Time-to-Completion. Fig. 3 presents the mean task completion time for Groups 1 and 2 in the four rounds of experiments. Note that the groups switched their means of instruction in Round 4, and thus, the results of Round 4 are analyzed separately later. Results of the two-sample *t*-test presented in Table 1 indicate a statistically significant difference between the mean time-to-completion achieved by participants in Groups 1 and 2 in Rounds 2 and 3. Note that Round 4 comparisons are not included because the means of instruction is swapped in that round (see Section 3.1). That is, 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. As a result, hypothesis H1 is rejected. The authors speculate that the participants in Group 2 (paper) gradually transitioned from following the task information (*i.e.*, assembly steps, 2D CAD drawing) to relying more on their memory to complete the task, while Group 1 (AR) still had to browse through the AR app and attend to the videos, vocal cues, animations, *etc*. It must be noted, however, that the performance of Group 1 was slightly affected by their unfamiliarity with the HoloLens 2 hardware and the AR app along with some technical issues during the experiments.

Number of Errors. The mean number of errors made by each group during rounds one through four of experiments is shown in Fig. 3. The two-sample *t*-test results presented in Table 2 indicate that Group 2 (paper) made a significantly higher mean number of errors compared to Group 1 in Round 3 of the experiments (the *p*-value of Round 2 is also near α). Note that Round 4 comparisons are not included because the means of instruction is swapped in that round. That is 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. These findings partially accept hypothesis H2. These findings underscore the significant impact of spatiotemporal alignment of task information and visual/vocal cues with experience on the number of errors made during task performance. Common errors made by participants in each group during Rounds 1–3 are as follows. *Group 1*: Incomplete insertion of parts, incorrect placement of spacers and washers, incorrect orientation/alignment of parts. *Group 2*: Incomplete, incorrect, or mixed-up insertion of parts (*e.g.*, spacers, washers, wires, retainer rings, screws), some parts left unassembled, incorrect orientation/alignment of parts, incorrect sequence of installation.

Help-Seeking Behavior. Neither group showed considerable help-

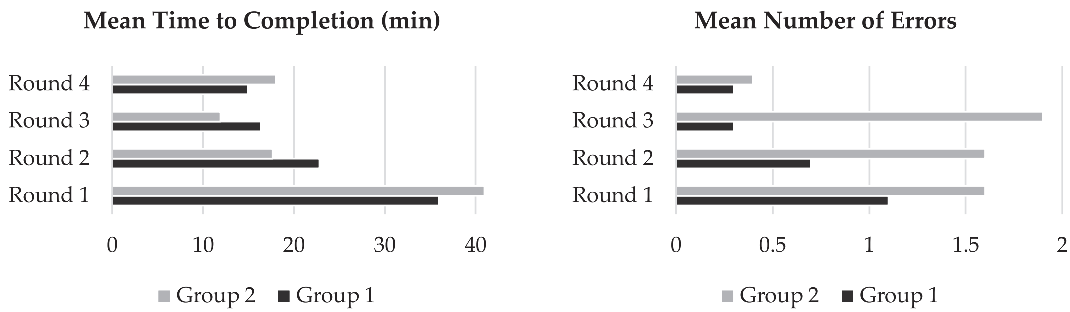

Fig. 3. Mean time-to-completion (left) and mean number of errors (right) for Groups 1 (AR-enabled) and 2 (paper-based) in Rounds 1–4.

Table 1
Two-sample *t*-test on mean time-to-completion in Rounds 1–3 ($\alpha = 0.05$).

Statistics	Round 1	Round 2	Round 3
Mean (*Group 1*, *Group 2*)	35.94, 41.01	22.80, 17.64	17.34, 11.90
df	18	18	18
t-Statistic	−0.85	1.90	2.44
p-value	0.20	**0.04**	**0.01**

Table 2
Two-sample *t*-test on the mean numbers of errors ($\alpha = 0.05$).

Statistics	Round 1	Round 2	Round 3
Mean (*Group 1*, *Group 2*)	1.10, 1.60	0.70, 1.60	0.30, 1.90
Df	18	18	18
t-Statistic	−0.85	−1.45	−2.50
p-value	0.20	0.08	**0.01**

seeking behavior. Only two participants from each group requested help related to AR app, part orientation, and sequence of assembly. The observed lack of help-seeking behavior is consistent with the observation 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. The findings indicate no relationship between the means of task information delivery and help-seeking behavior, and therefore, hypothesis H3 is rejected.

Learning Curve. Paired *t*-test was conducted to study the statistical significance of 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. The results shown in Table 3 indicate significant reductions in mean time-to-completion between each round for both groups. Thus, it is concluded that the means of instruction (*i.e.*, paper versus AR) does not have any noticeable impact on task completion time. However, the results of paired *t*-test on the mean number of errors presented in Table 4 indicate 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

Table 3
Paired *t*-test on the mean time-to-completion of each group between Rounds 1 and 2, Rounds 2 and 3, and Rounds 1 and 3 ($\alpha = 0.05$).

Statistics	Group 1			Group 2		
	Rounds 1–2	*Rounds 2–3*	*Rounds 1–3*	*Rounds 1–2*	*Rounds 2–3*	*Rounds 1–3*
Mean	35.94, 22.80	22.80, 16.39	35.94, 16.39	41.01, 17.64	17.64, 11.90	41.01, 11.90
Pearson	0.43	0.61	0.46	0.13	0.71	0.35
df	9	9	9	9	9	9
t-Statistic	4.75	3.58	7.75	4.47	5.13	5.95
p-value	**0.0005**	**0.002**	**1.42E-05**	**0.0008**	**0.0003**	**0.0001**

Table 4
Paired *t*-test on the mean number of errors by each group between Rounds 1 and 2, Rounds 2 and 3, and Rounds 1 and 3 ($\alpha = 0.05$).

Statistics	Group 1			Group 2		
	Rounds 1–2	*Rounds 2–3*	*Rounds 1–3*	*Rounds 1–2*	*Rounds 2–3*	*Rounds 1–3*
Mean	1.10, 0.70	0.7, 0.3	1.10, 0.30	1.60, 1.60	1.60, 1.90	1.60, 1.90
Pearson	0.31	−0.31	−0.30	0.69	0.81	0.74
df	9	9	9	9	9	9
t-Statistic	1.18	1.18	2.06	0	−0.82	−0.71
p-value	0.13	0.13	**0.03**	0.5	0.22	0.25

between Rounds 1 and 3. Accordingly, it is concluded that not only AR-based task information delivery leads to fewer errors, but it also helps workers significantly reduce the number of errors in subsequent rounds of operation. Thus, hypothesis H4 is accepted. Note that similar to the results presented in Tables 1 and 2, Round 4 comparisons are not included in the analysis because the means of instruction is swapped in that round.

Independence from AR. Results of paired *t*-test on the mean time-to-completion of each group in Round 3 and Round 4 indicate two interesting observations (see Table 5): (1) Group 1 participants, who switched from AR guides in Round 3 to paper guides in Round 4, were able to complete their task even slightly faster in Round 4 than in Round 3, although the difference between mean completion times is not statistically significant. Here is a quote from one of the Group 1 participants after completing Round 4 of the experiments: "*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.*" (2) Group 2, however, demonstrated significantly longer completion times in Round 4 using AR than in Round 3 using paper, which is partly attributed to their lack of prior experience with HoloLens 2 and the AR app. Furthermore, results of paired *t*-test on the mean

Table 5
Paired *t*-test on mean time-to-completion and number of errors by each group between Rounds 3 and 4, after switching means of task information delivery ($\alpha = 0.05$).

Statistics	Mean Time-to-Completion		Mean Number of Errors	
	Group 1	*Group 2*	*Group 1*	*Group 2*
Mean	16.39, 14.91	11.90, 18.03	0.30, 0.30	1.90, 0.40
Pearson	0.80	−0.002	0.38	0.27
df	9	9	9	9
t-Statistic	1.67	−2.14	0	2.50
p-value	0.06	**0.03**	0.5	**0.02**

number of errors made by each group during Rounds 3 and 4 (Table 5) indicate that: (1) Group 1 maintained their relatively lower mean number of errors (0.3) in Round 4 even after a few days gap and without AR support. (2) The mean number of errors made by Group 2 in Round 4 was significantly reduced after switching from paper to AR compared to Round 3 and Round 2. These findings point to the impacts of AR on accelerating workers' learning and competency, its usefulness for traditionally trained workers (*e.g.*, Group 2) 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. Hence, hypothesis H5 is accepted.

4.2. Qualitative questionnaires

Results of the NASA-TLX questionnaire shown in Fig. 4 indicate that both groups experienced almost identical levels of mental demand, physical demand, temporal demand, perceived performance, effort, and frustration. Thus, hypothesis H6 is rejected. In general, the assembly task was perceived not too challenging by the participants, and they were generally satisfied with their performance.

Fig. 5 shows the participant responses to questions about the impacts of different modes of AR (*i.e.*, text, 3D animation, and video) on task performance, their independence from AR, and their experience with HoloLens 2. The participants had different preferences for the three modes of AR task information delivery. Some participants found the combination of text and 3D CAD animation more helpful than the expert capture videos. Examples of feedback comments by those participants are:

> *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.*
> *Today I turned off the video and relied on the text's part numbers and the 3D model to complete the assembly. Since I already knew how each part fit together, the text and 3D model ensured I had the correct part and the correct orientation respectively. This made the assembly quite easy to finish.*
> *The video was only helpful in describing what order washers 2 and 3 go and which way to screw on parts 25. Otherwise, the text and CAD helped the most.*
> *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.*

These participants appear to have learned mostly from the spatial representation of the parts and assembly process through interactive 3D CAD animations along with textual instructions to ensure correct selection, alignment, and insertion of the parts. Some other participants, however, reported videos with vocal cues in conjunction with textual instructions as their preferred mode of AR guides. These participants preferred observing and imitating how an expert performs the task (*i.e.*, learning from demonstration) as their primary mechanism to learn the task:

> *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 mostly watched the video but referred to the CAD model when confused. Lastly, I checked part numbers with the written instructions.*
> *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.*
> *The audio instructions from the video were most helpful to me because I already knew about the part. I had some trouble manipulating the CAD model, but it was also a helpful aid.*

The participants were also asked to rate their independence from the AR guides. Group 1 participants were initially highly dependent upon AR. Specifically, 70% of the participants reported high or very high dependence upon AR. However, they gradually became more independent from AR as only 20% of them were highly or very highly dependent on AR at the end of Round 3. On the other hand, 90% of the participants from Group 2, who switched from paper to AR in Round 4, stated that they are highly independent from AR. Yet, as discussed earlier, switching to AR helped this group significantly reduce the number of errors made during assembly. Furthermore, most participants found HoloLens comfortable and easy to use; however, the study participants are all young and educated engineering students and the manufacturing workforce may not have the same perception. In fact, one of the main concerns of our industry partner was that the technology may be intimidating and difficult to adopt for most of their senior workers. Moreover, only 10% of the participants expressed a preference to be trained by a person rather than the AR app. Again, it must be noted that actual manufacturing workers may have different opinions and preferences.

The participants were also asked to provide general suggestions for using AR as a training or assistive tool in manufacturing based on their experience with AR. Some key suggestions are as follows: (1) text-to-speech features to read out the textual instructions, and also the use of voice commands for hands-free interaction with the AR content, (2) menu-based, non-procedural provision of task information so the user can call certain instructions on demand, rather than having to go through a fixed sequence of steps, (3) more interactive and personalizable layout design for the AR app so the user can use the layout they feel most comfortable in, and (4) a help option where the user can get assistance when something goes wrong or if they have a question about the task.

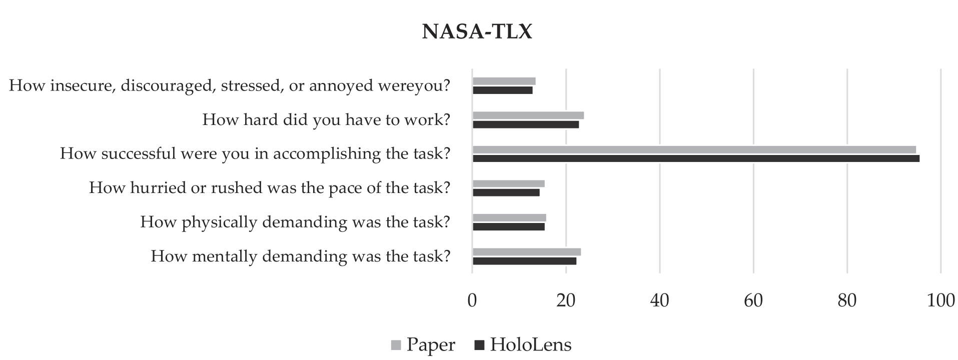

Fig. 4. NASA-TLX responses from both groups.

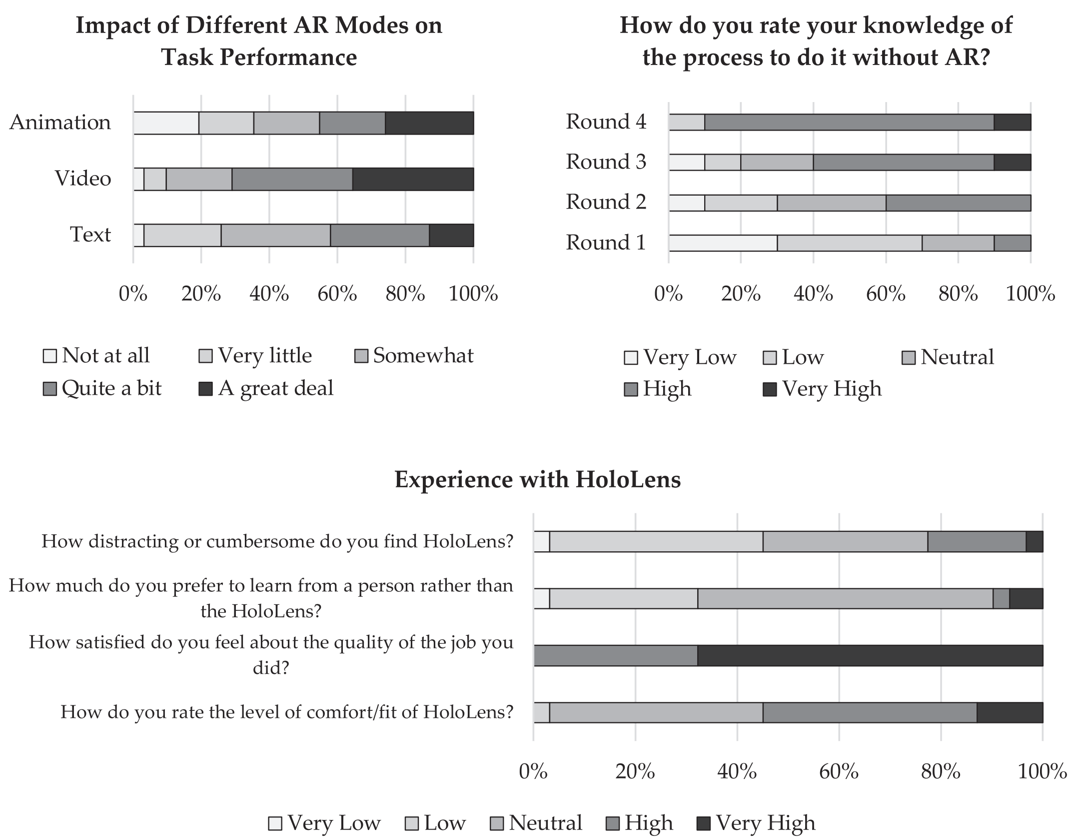

Fig. 5. Summary of qualitative questionnaire results on preferred AR modes, independence from AR, and experience with HoloLens. Note that the means of instruction was swapped between Round 3 and Round 4 (see Section 3.1).

4.3. Expert interviews

Several key insights were drawn from the interviews with 10 experts from industry, research institutions, and community colleges:

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 (tech-savvy) 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 (*e.g.*, hand gestures, manipulation of holograms) 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 (*e.g.*, limited English proficiency) 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) Successful industry adoption of AR 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 app developed in this study belongs to one out of hundreds of different subassemblies made by one manufacturer. The designs are also updated on a regular basis. The question then becomes: How do we author AR guides for these hundreds of different parts in a way that allows on-site engineers with no background in AR content development to maintain and update them in line with their regular design updates?
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 [64,65] 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.

It is evident that 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. Nevertheless, industrial AR 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 multidisciplinary research topics and questions that need to be addressed to realize the full potentials of AR as a *useful* tool for incumbent and future manufacturing workers.

5. Discussion

This paper is motivated by the three fundamental questions outlined in the Introduction section. This section discusses several challenges and insights associated with each research question and provides recommendations for future research in each area.

Q1. *What is the most effective way of delivering various task information to the worker? What are their impacts on their efficiency, number of errors, learning, independence, and cognitive load?* The laboratory experiments highlighted the importance of tailoring AR guides to the unique needs of individuals, which may drastically vary depending on their personal preferences and knowledge of the task. Responses to the qualitative questionnaires indicate that participants may have completely opposite sentiments about the same affordance of AR. Learning sciences research underscores the necessity of devising scaffolding mechanisms that align AR instructions to the learner's attention and cognitive processes to help them construct knowledge [40–42]. It is therefore critical to understand the nature of the scaffolding that AR affords, and how to design it in the most effective ways for the ongoing success of individual workers. Future research must therefore focus on transitioning from procedural, one-size-fits-all delivery of task information through AR to intelligent AR systems that dynamically scaffold AR guides to the subject matters that individual workers need training on. New methods are indeed required to interpret, predict, and guide the behavior of AR-supported manufacturing workers through adaptive scaffolding of instructions to the expertise level of individual workers. Results of the laboratory experiments also indicate that most participants developed absolute independence from AR after two or three assembly cycles, which points to the effectiveness of AR in improving task competency, and yet its low utility as an *assistive* tool for routine tasks such as the fuel cell module assembly used in the experiments. Hence, it is essential to develop a formalism of AR use-cases in manufacturing, and clearly differentiate training use-cases from use-cases where AR is utilized by manufacturing workers as an assistive *tool* during operation.

Q2. *What are the affordances of AR as a training tool prior to task performance* versus *as an assistive tool during task performance?* According to a recent report by MIT [66], the newer wave of automation in manufacturing is not so much to replace workers but rather to increase precision, safety, and product quality. Large firms continue to automate tasks that are "dirty, dull, and dangerous," but preserve "value-added" tasks that are the more desirable parts of manufacturing workers' jobs. Those kinds of value-added jobs are the jobs that are hard to automate, either because they require sophisticated and precise manipulation of physical objects that only a human is capable of (*e.g.*, the fuel cell module assembly task) or because they require complex reasoning and decision-making that machines are not capable of, *yet*. In this context, AR can be used as a *training* tool if the task involves relatively complex manipulation of physical objects but does not require a considerable level of reasoning or decision-making (see Fig. 6). Mechanical assembly is a good example of such tasks—an assembler typically does not need to analyze unseen scenarios or make difficult decisions, but to precisely follow and implement the assembly procedure. In such cases, the worker may learn and master the task via AR and then perform the task without the AR support.

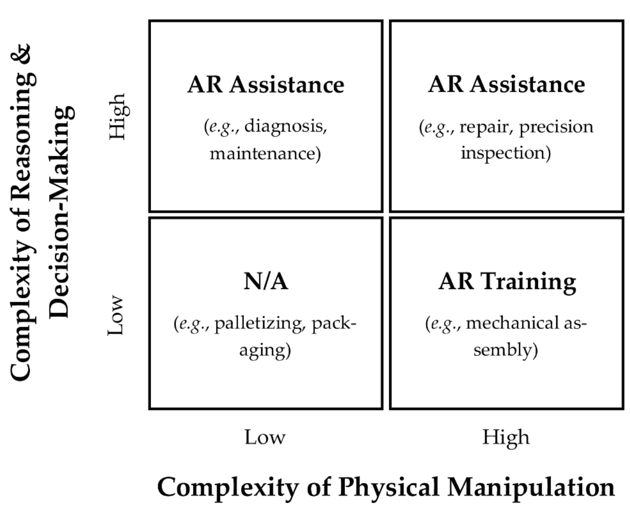

Fig. 6. Applications of AR in manufacturing tasks with different levels of variety and worker choice complexity.

If the task involves complex reasoning and decision-making, however, AR can serve as an effective tool for providing intelligent and personalized guidance, notifications, and task information, on-demand, during task performance, regardless of the complexity of physical manipulation (Fig. 6). Maintenance and inspection are good use-cases for AR assistants. In precision machining, for example, complex parts must be recurrently inspected using a wide range of gages under unchanged conditions. An adept inspector must have an in-depth knowledge of materials, processes, and equipment, and the necessary skills to continually measure and analyze gage readings and product manufacturing information to make proper decisions (*e.g.*, offsetting the machine, reworking, or scraping the part). In such environments, AR technology can be deployed as an assistive tool to provide personalized and on-demand performance support to enhance the learning and adaptability of workers to succeed in complex, dynamic work environments. Future research must therefore develop intelligent AR systems that leverage various sources of data streams from industrial IoT and smart manufacturing equipment, digital thread, and smart AR devices (*e.g.*, HoloLens) to continuously monitor the status of work and support worker's reasoning and decision-making processes through adaptive and personalized delivery of task information, smart notifications, and interactive features such as help options, question-answering, or remote assistance. It is important to note that these claims and the classification presented in Fig. 6 are based solely on the authors' knowledge and judgment.

Q3. *How can future AR technologies transition from passive delivery of task information to intelligent and proactive teaming with the worker?* As discussed earlier, state-of-the-art AR solutions offer limited personalized interactions between workers and AR, and predominantly provide 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 [14,16,63], and also hinder industry adoption. The provision of procedural knowledge [61] 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, quality assurance guidelines and 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, especially in tasks that involve complex reasoning and decision-making (*e.g.*, inspection, repair). 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 important to devise and examine new methods at the intersection of AI, AR, and human–machine interaction to advance the fundamental understanding of how new sources of multimodal data captured by AR devices, combined with digital thread, IoT, and cloud-based analytics, can be harnessed to interpret, predict, and guide the behavior of future manufacturing workers through intelligent worker-AR teaming. The integration of AR and digital twin technology [67] can create breakthrough possibilities to bridge the gap the rich, data-driven insights drawn from digital twins and the task performance and decisions of workers supported by AR.

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.

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. 2026618. 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. We acknowledge the support of our advisory committee and industry partners. We also thank our smart and dedicated students, Madeline Hulse, Ezra Frank, and Kumar Prashant Shaha who supported the development of the AR app and administration of the laboratory experiments.

Declaration of interests.

Mohsen Moghaddam reports financial support was provided by Northeastern University. Mohsen Moghaddam reports a relationship with National Science Foundation that includes: funding grants.

References

[1] S. N. Houseman, "Understanding the Decline of U.S. Manufacturing Employment ," Upjohn Institute Working Paper 18-287, Kalamazoo, MI, 2018, doi: 10.17848/wp18-287.
[2] NAM, "NAM Manufacturers' Outlook Survey," 2020. https://www.nam.org/wp-content/uploads/2020/09/NAM-Outlook-Survey-Q3-2020.pdf (accessed Mar. 17, 2021).
[3] S. Lund et al., "Risk, resilience, and rebalancing in global value chains," McKinsey & Company, 2020. https://www.mckinsey.com/business-functions/operations/our-insights/risk-resilience-and-rebalancing-in-global-value-chains (accessed Mar. 17, 2021).
[4] E. Brynjolfsson and A. McAfee, The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W W Norton & Co., 2014. Accessed: Mar. 10, 2021. [Online]. Available: https://psycnet.apa.org/record/2014-07087-000.
[5] SHRM, "Preparing for an Aging Workforce: Manufacturing Industry Report," Society for Human Resource Management, 2015.
[6] NAP, Building America's Skilled Technical Workforce (National Academies of Sciences, Engineering, and Medicine). National Academies Press, 2017. doi: 10.17226/23472.
[7] G. Giffi, P. Wellener, B. Dollar, H. Ashton Manolian, L. Monck, and C. Moutray, "Deloitte and The Manufacturing Institute skills gap and future of work study," 2018. [Online]. Available: http://www.themanufacturinginstitute.org/~/media/E323C4D8F75A470E8C96D7A07F0A14FB/DI_2018_Deloitte_MFI_skills_gap_FoW_study.pdf.
[8] S. Helper, E. Reynolds, D. Traficonte, and A. Singh, "Manufacturing in America: A View from the Field," MIT Work of the Future, 2021. https://workofthefuture.mit.edu/wp-content/uploads/2020/11/2020-Research-Brief-Berger.pdf (accessed Mar. 17, 2021).
[9] PTC, "Closing the Industrial Skills Gap with Industrial Augmented Reality," PTC, 2019. https://www.ptc.com/en/resources/augmented-reality/ebook/closing-the-industrial-skills-gap-with-augmented-reality (accessed Feb. 19, 2020).
[10] S. Conway, "The Total Economic Impact TM Of PTC Vuforia: Cost Savings And Business Benefits Enabled By Industrial Augmented Reality," 2019. [Online]. Available: https://www.ptc.com/en/resources/augmented-reality/report/forrester-total-economic-impact.
[11] D. Mizell, "Boeing's wire bundle assembly project," in Fundamentals of wearable computers and augmented reality, W. Barfield and T. Caudell, Eds. CRC Press, 2001, pp. 447–467.
[12] B. Schwald et al., "STARMATE: Using Augmented Reality technology for computer guided maintenance of complex mechanical elements," in E-work and e-commerce-novel solutions and practices for a global networked economy, B. Smith and E. Chiozza, Eds. 2001, pp. 196–202.
[13] B. Schwald, B.D. Laval, An augmented reality system for training and assistance to maintenance in the industrial context, in: in *International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision (WSCG)*, 2003, pp. 425–432.
[14] S. Webel, U. Bockholt, T. Engelke, N. Gavish, M. Olbrich, C. Preusche, An augmented reality training platform for assembly and maintenance skills, Rob. Auton. Syst. 61 (4) (Apr. 2013) 398–403, https://doi.org/10.1016/j.robot.2012.09.013.
[15] A. Syberfeldt, O. Danielsson, M. Holm, L. Wang, Visual Assembling Guidance Using Augmented Reality, Procedia Manuf. 1 (Jan. 2015) 98–109, https://doi.org/10.1016/j.promfg.2015.09.068.
[16] M. Holm, O. Danielsson, A. Syberfeldt, P. Moore, L. Wang, Adaptive instructions to novice shop-floor operators using Augmented Reality, Journal of Industrial and Production Engineering 34 (5) (Jul. 2017) 362–374, https://doi.org/10.1080/21681015.2017.1320592.
[17] B. Marr, "The Amazing Ways Honeywell Is Using Virtual And Augmented Reality To Transfer Skills To Millennials," Forbes, 2018. https://www.forbes.com/sites/bernardmarr/2018/03/07/the-amazing-ways-honeywell-is-using-virtual-and-augmented-reality-to-transfer-skills-to-millennials/#586ec524536a (accessed Feb. 19, 2020).
[18] T. Polladino, "Porsche Adopts Atheer's AR Platform to Connect Mechanics with Remote Experts « Next Reality," Next Reality, 2017. https://next.reality.news/news/porsche-adopts-atheers-ar-platform-connect-mechanics-with-remote-experts-0181255/ (accessed Feb. 19, 2020).
[19] R. O'Donnell, "How Mercedes-Benz uses augmented reality to train employees of all types," HRDive, 2018. https://www.hrdive.com/news/how-mercedes-benz-uses-augmented-reality-to-train-employees-of-all-types/530425/ (accessed Feb. 19, 2020).
[20] P. Vanneste, Y. Huang, J. Y. Park, F. Cornillie, B. Decloedt, and W. van den Noortgate, "Cognitive support for assembly operations by means of augmented reality: an exploratory study," International Journal of Human Computer Studies, vol. 143, no. October 2019, p. 102480, 2020, doi: 10.1016/j.ijhcs.2020.102480.
[21] Z.H. Lai, W. Tao, M.C. Leu, Z. Yin, Smart augmented reality instructional system for mechanical assembly towards worker-centered intelligent manufacturing, J. Manuf. Syst. 55 (February) (2020) 69–81, https://doi.org/10.1016/j.jmsy.2020.02.010.
[22] J.C. Arbeláez, R. Viganò, G. Osorio-Gómez, Haptic Augmented Reality (HapticAR) for assembly guidance, Int. J. Interact. Des. Manuf. 13 (2) (2019) 673–687, https://doi.org/10.1007/s12008-019-00532-3.
[23] J.A. Erkoyuncu, I.F. del Amo, M. Dalle Mura, R. Roy, G. Dini, Improving efficiency of industrial maintenance with context aware adaptive authoring in augmented reality, CIRP Ann. – Manuf. Technol. 66 (1) (2017) 465–468, https://doi.org/10.1016/j.cirp.2017.04.006.
[24] C.Y. Siew, S.K. Ong, A.Y.C. Nee, A practical augmented reality-assisted maintenance system framework for adaptive user support, Rob. Comput. Integr. Manuf. 59 (Oct. 2019) 115–129, https://doi.org/10.1016/j.rcim.2019.03.010.
[25] U. Urbas, R. Vrabič, N. Vukašinović, Displaying product manufacturing information in augmented reality for inspection, Procedia CIRP 81 (2019) 832–837, https://doi.org/10.1016/j.procir.2019.03.208.
[26] J. Polvi, T. Taketomi, A. Moteki, T. Yoshitake, T. Fukuoka, G. Yamamoto, C. Sandor, H. Kato, Handheld Guides in Inspection Tasks: Augmented Reality versus Picture, IEEE Trans. Visual Comput. Graphics 24 (7) (2018) 2118–2128, https://doi.org/10.1109/TVCG.2017.2709746.
[27] J. M. Runji and C. Y. Lin, "Markerless cooperative augmented reality-based smart manufacturing double-check system: Case of safe PCBA inspection following automatic optical inspection," Robotics and Computer-Integrated Manufacturing, vol. 64, no. February 2019, p. 101957, 2020, doi: 10.1016/j.rcim.2020.101957.
[28] J. Zhu, S.K. Ong, A.Y.C. Nee, A context-aware augmented reality assisted maintenance system, Int. J. Comput. Integr. Manuf. 28 (2) (2015) 213–225, https://doi.org/10.1080/0951192X.2013.874589.
[29] L. Angrisani, P. Arpaia, A. Esposito, N. Moccaldi, A Wearable Brain-Computer Interface Instrument for Augmented Reality-Based Inspection in Industry 4.0, IEEE Trans. Instrum. Meas. 69 (4) (2020) 1530–1539, https://doi.org/10.1109/TIM.1910.1109/TIM.2019.2914712.
[30] M. Gattullo, G. W. Scurati, M. Fiorentino, A. E. Uva, F. Ferrise, and M. Bordegoni, "Towards augmented reality manuals for industry 4.0: A methodology," Robotics and Computer-Integrated Manufacturing, vol. 56, no. August 2018, pp. 276–286, 2019, doi: 10.1016/j.rcim.2018.10.001.
[31] T. Wang, et al., CAPturAR: An augmented reality tool for authoring human-involved context-aware applications, in: in *UIST 2020 - Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology*, 2020, pp. 328–341, https://doi.org/10.1145/3379337.3415815.
[32] Y. Cao et al., "GhostAR: A Time-space Editor for Embodied Authoring of Human-Robot Collaborative Task with Augmented Reality," 2019. Accessed: Feb. 06, 2021. [Online]. Available: https://doi.org/10.1145/3332165.3347902.
[33] Y. Wang, S. Zhang, B. Wan, W. He, X. Bai, Point cloud and visual feature-based tracking method for an augmented reality-aided mechanical assembly system, Int. J. Adv. Manuf. Technol. 99 (9–12) (2018) 2341–2352, https://doi.org/10.1007/s00170-018-2575-8.
[34] X. Wang, S.K. Ong, A.Y.C. Nee, Multi-modal augmented-reality assembly guidance based on bare-hand interface, Adv. Eng. Inf. 30 (3) (2016) 406–421, https://doi.org/10.1016/j.aei.2016.05.004.
[35] J. Blattgerste, B. Strenge, P. Renner, T. Pfeiffer, K. Essig, "Comparing conventional and augmented reality instructions for manual assembly tasks", *ACM International Conference Proceeding Series*, vol, Part F1285 (2017) 75–82, https://doi.org/10.1145/3056540.3056547.
[36] O. Danielsson, A. Syberfeldt, M. Holm, L. Wang, Operators perspective on augmented reality as a support tool in engine assembly, Procedia CIRP 72 (2018) 45–50, https://doi.org/10.1016/j.procir.2018.03.153.
[37] D. Mourtzis, A. Vlachou, V. Zogopoulos, Cloud-based augmented reality remote maintenance through shop-floor monitoring: A product-service system approach, J. Manuf. Sci. Eng., Trans. ASME 139 (6) (2017) 1–11, https://doi.org/10.1115/1.4035721.
[38] S.J. Hu, X. Zhu, H. Wang, Y. Koren, Product variety and manufacturing complexity in assembly systems and supply chains, CIRP Ann. – Manuf. Technol. 57 (1) (2008) 45–48, https://doi.org/10.1016/j.cirp.2008.03.138.
[39] N. Orfi, J. Terpenny, A. Sahin-Sariisik, Harnessing product complexity: Step 1establishing product complexity dimensions and indicators, Eng. Economist 56 (1) (2011) 59–79, https://doi.org/10.1080/0013791X.2010.549935.
[40] K.R. Bujak, I. Radu, R. Catrambone, B. MacIntyre, R. Zheng, G. Golubski, A psychological perspective on augmented reality in the mathematics classroom, Comput. Educ. 68 (2013) 536–544, https://doi.org/10.1016/j.compedu.2013.02.017.

[41] J.M. Zydney, Z. Warner, Mobile apps for science learning: Review of research, Comput. Educ. 94 (Mar. 2016) 1–17, https://doi.org/10.1016/j.compedu.2015.11.001.

[42] M.B. Ibáñez, C. Delgado-Kloos, Augmented reality for STEM learning: A systematic review, Comput. Educ. 123 (April) (2018) 109–123, https://doi.org/10.1016/j.compedu.2018.05.002.

[43] X. Wang, S.K. Ong, A.Y.C. Nee, A comprehensive survey of augmented reality assembly research, Adv. Manuf. 4 (1) (Mar. 2016) 1–22, https://doi.org/10.1007/s40436-015-0131-4.

[44] I. Fernández del Amo, J.A. Erkoyuncu, R. Roy, R. Palmarini, D. Onoufriou, A systematic review of Augmented Reality content-related techniques for knowledge transfer in maintenance applications, Comput. Ind. 103 (2018) 47–71, https://doi.org/10.1016/j.compind.2018.08.007.

[45] R. Palmarini, J. A. Erkoyuncu, R. Roy, and H. Torabmostaedi, "A systematic review of augmented reality applications in maintenance," Robotics and Computer-Integrated Manufacturing, vol. 49, no. July 2017, pp. 215–228, 2018, doi: 10.1016/j.rcim.2017.06.002.

[46] T. Masood, J. Egger, Augmented reality in support of Industry 4.0—Implementation challenges and success factors, Rob. Comput. Integr. Manuf. 58 (Aug. 2019) 181–195, https://doi.org/10.1016/j.rcim.2019.02.003.

[47] J. Egger and T. Masood, "Augmented reality in support of intelligent manufacturing – A systematic literature review," Computers and Industrial Engineering, vol. 140. Elsevier Ltd, p. 106195, Feb. 01, 2020. doi: 10.1016/j.cie.2019.106195.

[48] K. Koumaditis, S. Venckute, F. S. Jensen, and F. Chinello, "Immersive Training: Outcomes from Small Scale AR/VR Pilot-Studies," 26th IEEE Conference on Virtual Reality and 3D User Interfaces, VR 2019 - Proceedings, vol. 2019-January, pp. 1894–1898, Mar. 2019, doi: 10.1109/VR44988.2019.9044162.

[49] S. Werrlich, A. Daniel, A. Ginger, P. A. Nguyen, and G. Notni, "Comparing HMD-Based and Paper-Based Training," Proceedings of the 2018 IEEE International Symposium on Mixed and Augmented Reality, ISMAR 2018, pp. 134–142, Jan. 2019, doi: 10.1109/ISMAR.2018.00046.

[50] E. Smith, K. McRae, G. Semple, H. Welsh, D. Evans, and P. Blackwell, "Enhancing Vocational Training in the Post-COVID Era through Mobile Mixed Reality," Sustainability 2021, Vol. 13, Page 6144, vol. 13, no. 11, p. 6144, May 2021, doi: 10.3390/SU13116144.

[51] T. Masood, J. Egger, Adopting augmented reality in the age of industrial digitalisation, Comput. Ind. 115 (2020) 103112, https://doi.org/10.1016/j.compind.2019.07.002.

[52] S. Werrlich, P. A. Nguyen, and G. Notni, "Evaluating the training transfer of Head-Mounted Display based training for assembly tasks," ACM International Conference Proceeding Series, pp. 297–302, Jun. 2018, doi: 10.1145/3197768.3201564.

[53] D. Brice, K. Rafferty, and S. McLoone, "AugmenTech: The Usability Evaluation of an AR System for Maintenance in Industry," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 12243 LNCS, pp. 284–303, Sep. 2020, doi: 10.1007/978-3-030-58468-9_21.

[54] Z. B. Wang, S. K. Ong, and A. Y. C. Nee, "Augmented reality aided interactive manual assembly design," The International Journal of Advanced Manufacturing Technology 2013 69:5, vol. 69, no. 5, pp. 1311–1321, Jun. 2013, doi: 10.1007/S00170-013-5091-X.

[55] G. Westerfield, A. Mitrovic, and M. Billinghurst, "Intelligent Augmented Reality Training for Motherboard Assembly," International Journal of Artificial Intelligence in Education 2014 25:1, vol. 25, no. 1, pp. 157–172, Nov. 2014, doi: 10.1007/S40593-014-0032-X.

[56] C. K. Sahu, C. Young, and R. Rai, "Artificial intelligence (AI) in augmented reality (AR)-assisted manufacturing applications: a review," https://doi.org/10.1080/00207543.2020.1859636, 2020, doi: 10.1080/00207543.2020.1859636.

[57] O. Noroozi, P. A. Kirschner, H. J. A. Biemans, and M. Mulder, "Promoting Argumentation Competence: Extending from First- to Second-Order Scaffolding Through Adaptive Fading," Educational Psychology Review, vol. 30, no. 1. Springer New York LLC, pp. 153–176, Mar. 01, 2018. doi: 10.1007/s10648-017-9400-z.

[58] V.M. Cabello, M.E.S. Lohrmann, Fading scaffolds in stem: Supporting students' learning on explanations of natural phenomena, Adv. Intell. Syst. Comput. 596 (2018) 350–360, https://doi.org/10.1007/978-3-319-60018-5_34.

[59] B.R. Belland, A.E. Walker, N.J. Kim, M. Lefler, Synthesizing Results From Empirical Research on Computer-Based Scaffolding in STEM Education: A Meta-Analysis, Rev. Educ. Res. 87 (2) (Apr. 2017) 309–344, https://doi.org/10.3102/0034654316670999.

[60] T.C. Lin, Y.S. Hsu, S.S. Lin, M.L. Changlai, K.Y. Yang, T.L. Lai, A review of empirical evidence on scaffolding for science education, Int. J. Sci. Mathem. Educ. 10 (2) (Apr. 2012) 437–455, https://doi.org/10.1007/s10763-011-9322-z.

[61] I. Becerra-Fernandez, R. Sabherwal, Knowledge management: Systems and processes, Routledge, 2014.

[62] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research," Advances in Psychology, vol. 52, no. C, pp. 139–183, Jan. 1988, doi: 10.1016/S0166-4115(08)62386-9.

[63] I. Radu, Augmented reality in education: A meta-review and cross-media analysis, Pers. Ubiquit. Comput. 18 (6) (Jan. 2014) 1533–1543, https://doi.org/10.1007/s00779-013-0747-y.

[64] S.P. Frechette, A.T. Jones, B.R. Fischer, Strategy for testing conformance to geometric dimensioning & tolerancing standards, Procedia CIRP 10 (Jan. 2013) 211–215, https://doi.org/10.1016/j.procir.2013.08.033.

[65] T. Hedberg, J. Lubell, L. Fischer, L. Maggiano, and A. B. Feeney, "Testing the digital thread in support of model-based manufacturing and inspection," Journal of Computing and Information Science in Engineering, vol. 16, no. 2, Jun. 2016, doi: 10.1115/1.4032697.

[66] D. Autor, D. Mindel, and E. Reynolds, "The Work of the Future: Building Better Jobs in an Age of Intelligent Machines," MIT Work of the Future, 2020. https://workofthefuture.mit.edu/research-post/the-work-of-the-future-building-better-jobs-in-an-age-of-intelligent-machines/ (accessed Mar. 17, 2021).

[67] S. Aheleroff, X. Xu, R.Y. Zhong, Y. Lu, Digital Twin as a Service (DTaaS) in Industry 4.0: An Architecture Reference Model, Adv. Eng. Inf. 47 (2021) 101225, https://doi.org/10.1016/j.aei.2020.101225.