Augmented Reality for Training and Operational Support Solutions

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ABSTRACT

A surfeit of opportunities exists to design advanced augmented reality (AR) training and operational support applications. As such, AR is positioned to subsume conventional training and formative assessment techniques traditionally reserved for classroom settings. To be effective, AR training and operational support solutions must allow trainees and/or operators to construct a unified body of knowledge that allows them to recognize problems and solve inferential questions about previously learned material. Yet, understanding how to transcribe AR content and associated assessments to meet desired learning outcomes in three-dimensional space remains relatively underexplored. AR training content design and assessments should be sensitive to trainees' needs as their knowledge base expands, while also carefully leveraging AR's multidimensional features, yet at the same time not overwhelming learners with extraneous information. This paper will review Bloom's taxonomy of cognitive processes and knowledge dimensions, the importance of memory encoding processes and stimulus-response compatibility, and assessment strategies to carve out a path for the development of robust AR training and operational support solutions. It is plausible that the pedagogical and design principles reviewed in this paper will provide a framework for developing AR training and operational support solutions that transition trainees and operators out of superficial learning and into deeper understanding of complex domains.

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INTRODUCTION

> *ET3 Smith has been tasked with learning how to perform a repair job on the Gerald R. Ford (CVN 78) aircraft carrier. He dons his augmented reality (AR) headset, which provides him with a familiarization module on the part that he will be repairing. The module starts with general information about the part, observation of a video-based repair of the part by an expert, and then provides an opportunity to locate problem components within the part and learn how they can breakdown. After the familiarization module is complete, ET3 Smith is required to complete an assessment, which involves a recognition-based assessment of steps or critical cues. As ET3 Smith answers each question, he is provided immediate feedback to reinforce his understanding of previously learned information. ET3 Smith then advances to the next level of training and learns about common procedures that are performed when repairing a faulty part via worked examples. After watching the training module, ET3 Smith is assessed on his ability to remember procedural steps, the consequences of incorrect steps, and potential alternative approaches to completing the procedure. As ET3 Smith masters descriptive knowledge about parts, concepts, procedures, and knowledge structures, his training will adapt and begin to furnish him with opportunities to apply, analyze, and evaluate problem-components in interactive training sessions.*

One can envision many such scenarios in which AR technology can be used to support training and operations. Augmented reality enhances the natural world with interactive virtual content and thus has many practical applications for classroom (Fleck, Hachet, & Bastien, 2015; Hsu, 2017; Ibáñez & Delgado-Kloos, 2018; Vilkoniene, 2009; Wojciechowski, R., & Cellary, 2013; Yip, Wong, Yick, Chan, & Wong, 2019) and industry-based training and operational support (Gavish et al., 2015; Hamza-Lup, Rolland, & Hughes, 2018; Leblanc et al., 2010; Vincenzi et al., 2003; Webel et al., 2013). Within augmented environments users are able to register spatial information through different sensory modalities, introducing new possibilities for conveying and assessing knowledge beyond conventional methods. AR is thought to be particularly well-suited to supporting learning of contextually rich tasks, as training programs are most effective when the original learning context is representative of the desired performance context (e.g., Tulving & Thompson 1973; Smith & Vela, 2001), known also as context-dependent memory (e.g., Godden & Baddeley, 1995). Yet, though immersive technology can create representative contexts to facilitate users' acquisition and transfer of knowledge (e.g., Najjar, 1998), poor instantiation of augmented content can monopolize attentional resources and disrupt learning (e.g., Mayer et al., 2008). As such, validated pedagogical and design techniques should motivate the development of

AR training and operational support to ensure that learning is reinforced, not obstructed. This paper will review Bloom's taxonomy of cognitive processes and knowledge dimensions, the importance of memory encoding processes and stimulus-response compatibility, and assessment strategies to carve out a path for the development of robust AR training and operational support solutions. The challenge is determining how best to use AR technology so that it empowers workers.

Bloom's (1956) taxonomy of educational objectives, which frames the development of knowledge into dimensions of cognitive processing, can be used as a guide to build effective AR training and operational support solutions. Specifically, the taxonomy serves as an effective structure for accommodating novice to expert learning needs when appropriately aligned with learning objectives, instructions, and assessments (Karthwohl, 2002).

- **Remember:** First, learners gather declarative knowledge of a subject matter (e.g., part names and types; default types, etc.) and recall such information when tested.
  - In the ET3 Smith example, as he was not familiar with the repair, the AR training started with a familiarization module to help him absorb declarative knowledge.
- **Comprehend:** Second, learners infer meaning from facts to explain and generalize concepts in a cogent manner.
  - A follow-on AR module, might involve ET3 Smith in worked examples so that he could start to understand how to use his newly acquired knowledge to assess the repair situation and hypothesize how best to proceed.
- **Apply:** Third, learners apply their understanding of material in a novel domain.
  - As ET3 Smith's knowledge advances, AR modules might involve ET3 Smith in troubleshooting situations that are similar to but distinct from a previously encountered scenario, selecting the proper course of action in the novel application, and carrying out appropriate variations on repair procedures for the new scenario.
- **Analyze:** Fourth, learners deconstruct information into constituent parts to differentiate between concepts and underlying principles.
  - As higher levels of expertise are approached, AR could be used to introduce troubleshooting scenarios that occur infrequently and require learners to codify broader troubleshooting approaches and skills.
- **Evaluate:** Fifth, learners manipulate information to justify a decision or evaluate a construct.
  - Complexity could be ratcheted up next, with AR scenarios that have multiple system faults to troubleshoot and repair.
- **Create:** Sixth, learners formalize new points of view based on their mastery of acquired information.
  - Finally, expert repairmen could be immersed in AR scenarios that garner their knowledge and use it to develop operational support for more junior repair personnel.

Bloom's (1956) taxonomy also includes four knowledge dimensions that represent the types of knowledge to be acquired: factual, conceptual, procedural, and meta-cognitive.

- **Factual knowledge** portends that elements of a particular subject matter, such as terminology or details, have been properly encoded in memory.
  - In AR, factual knowledge can be conveyed via videos, text overlays, audio segments and more.
- **Conceptual knowledge** is the understanding of how individual elements relate to one another and fit into a broader category.

  - AR can highlight individual elements in space and relate them to one another through color coding, story or other such user interaction elements.
- **Procedural knowledge** is ascertained when trainees understand how to select and perform techniques to complete a specific task.
  - AR can support walking a trainee through a procedure, highlighting important information each step of the way.
- **Meta-cognitive knowledge** develops as trainees become aware of their own cognition.
  - In AR, meta-cognitive knowledge could be fostered by allowing novices to observe the proficient use of a skill, say via a worked example, and including a story line that conveys the metacognitive strategies of virtual mentors, involving more proficient trainees in concept mapping and having them adapt strategies that are found to be ineffective, among other such techniques.

MEMORY ENCODING AND STIMULUS-RESPONSE COMPATIBILITY

While Bloom's (1956) taxonomy helps to define the cognitive processes and knowledge dimensions to train, there is a need to identify how to best encode this information in an AR training or operational support environment. In a broad sense, learning is a complex function that demands a partnership between a unique set of cognitive processes that connect fragments of information into valuable frames of knowledge and meaning. Specifically, Mayer (1997) proposed that the facilitation of technology-supported learning is supported by three encoding processes: selection, organization, and integration.

- First, **selection** occurs when learners inhibit extraneous information processing to encode relevant information in working memory.
- Learners then **organize** the selected information into a logical cognitive structure.
- Once a cognitive structure has been established, learners **integrate** their new knowledge by relating acquired information with existing knowledge from long-term memory. At this stage, transfer of learning takes place, where the acquired skills and knowledge in one domain are extrapolated to support performance in a similar (i.e., near transfer) or novel (i.e., far transfer) domain (Mayer & Wittrock, 2006).

For example, maintenance operations that require ET3 Smith to troubleshoot a problem by: 1) **selecting** the system the problem is originating from, 2) reconfiguring (**reorganizing**) the system to accomplish the repair objective, and 3) anticipating how the system outcome may vary under different conditions or explaining why the system is behaving in a certain manner based on **integration** of current information with prior knowledge, require these three stages of encoding (Mayer, 2001).

In AR, trainees could engage in these encoding processes through repeated interactions that encourage elaboration of augmented information; which in turn may foster the creation of multiple retrieval routes in memory for trainees to access on command (Elmes & Bjork, 1975; Greene & Stillwell, 1995; Hunt & Einstein, 1981). This elaborative processing is anticipated to occur as trainees create associations between augmented information presented via different sensory modalities, while also relating new information with existing information held in long-term memory. Such elaboration is known to increase learning and improve encoding and retention of new information (Fisher, 1981). The process of developing such multiple memory traces is known as encoding variability, which has also been found to produce greater retrieval benefits than using a single encoding strategy (Hintzman & Stern, 1978; Huff & Bodner, 2014). AR could readily support such encoding variability, presenting information via different sensory modalities. Yet, encoding variability can also come at a cost when multiple retrieval routes compete for access to a single knowledge structure. Young and Bellezza (1982), for example, tasked learners with memorizing a string of 80 words with either one or two mnemonics to assess if multiple retrieval pathways facilitated recall more than a single retrieval pathway. One group was presented with the same string of words twice and was tasked with using the same mnemonic for each presentation. The second group performed the same task but used two separate mnemonics to encode the word list. The authors confirmed that a single mnemonic produced a single pathway (i.e., encoding constancy) that better assisted with recall skills. In addition, the authors postulated that the creation of a single pathway during first exposure to information can be elaborated on during subsequent exposure, so long as two independent pathways are not in competition with one another. So rather than inundating trainees with multi-sensory information because it is technologically possible in immersive training and operational support solutions, AR can support optimization of this encoding process by applying the stimulus-response compatibility principle.

One benefit of an augmented training or operational support environment is that virtual stimuli can be presented through multi-modal sensory registers (visual, auditory, haptic, olfaction) and imposed on an existing real environment. The augmented stimuli are intended to enhance perception of and action on the real world through a merging of reality and virtuality (Milgram & Kishino, 1994). Yet, this augmentation must be synergistic to enhance the encoding processes of selection, organization, and integration. Specifically, responses to augmented objects in a real environment will be more effective (i.e., faster and more accurate) when the responses are designed to match features of the objects (Miles & Proctor, 2009). This mapping is known as stimulus-response (S-R) compatibility (Proctor & Vu, 2006), and there are three types of mappings (Miles & Proctor, 2009): conceptual (e.g., above and below; left and right), physical (e.g., auditory task stimuli mapped to verbal responses; spatial task stimuli mapped to manual responses), and structural (e.g., A-B-C mapped to 1-2-3). When augmented information is imposed upon the real environment in a manner that achieves S-R compatibility, the result will be enhanced perceptual sensitivity (e.g., stimulus features can be processed more efficiently and effectively; Stein & Stanford, 2008). When such S-R compatibility is not achieved during the merging of virtual and real, interference may occur during conceptual encoding, and with it the loss of anticipated performance gains (i.e., slower and less accurate responses; Seymour, 1977). That is, when the characteristic of a stimulus and response are optimally and intentionally matched, users are better able to make more rapid and accurate responses than if S-R pairings are unsystematic (Dutta & Proctor, 1992; Fitts & Seeger, 1953; Proctor & Vu, 2006). In addition, these affordances can help to establish strong design principles that relate virtual display formats to working memory processes, such as verbal and spatial working memory. Verbal working memory stores linguistic information, such as visual or vocal words and sounds, whereas spatial working memory stores information in an analog, spatial form, and is useful for orientation and localization tasks (Baddeley 1986, 1995). Thus, presenting augmented information either visually or audibly to a trainee or operator in a corresponding verbal or spatial compatible format, can support the development of a reservoir of task-related verbal and spatial long-term memory (see Wickens, Sandry, & Vidulich, 1983; Wickens, Hollands, Banbury, & Parasuraman, 2015). Moreover, requiring trainees to respond to augmented verbal or spatial stimuli in a compatible verbal or manual manner can help generate desired performance gains. The accuracy of these responses can, in turn, be assessed to support real-time feedback and remediation.

ASSESSMENT STRATEGIES

Augmented reality allows for assessment of performance in real time and subsequent adaptation of content based on proficiency. Embedding real-time assessments within interactive training programs allows trainees and instructors to gauge performance against a desired set of performance objectives and adapt training content accordingly. Real-time assessments can provide trainees with domain-specific feedback to highlight errors and provide remediation that conveys a path for corrective action during training. Such adaptive training is anticipated to lead to deeper conceptual knowledge encoding (the “why” associated with the “how”; Forbes-Riley & Litman, 2011). Further, Roediger, Putnam, and Smith (2011) identified that assessment results in better learning gains than reviews (Nungester & Duchastel, 1982), indirectly potentiates learning (Izawa, 1966), facilitates the organization of knowledge (Masson & McDaniel, 1981), supports the application of knowledge in novel contexts (Butler, 2010), helps to identify where knowledge is deficient (Amlund, Kardash, & Kuhlhavy, 1986), improves trainee’s awareness of self-cognition (Kornell & Son, 2009), and ameliorates potential conflicts when learning new information (Szpunar, McDermott, & Roediger, 2007). Yet, assessments are varied in how they solicit knowledge from trainees, and training paradigms should be careful not to make sweeping assumptions about the cognitive processes and knowledge dimensions they are intended to assess. For instance, short answer and essay style assessments typically involve effortful retrieval to generate a solution from vague or specific cues – a form of mental abstraction. In contrast, multiple choice and fill-in-the-blank assessments require less effortful retrieval because learners are better able to eliminate multiple choice options through pattern recognition. Taken together, Pyc and Rawson (2009) indicated that successful effortful retrieval (i.e., essay question) results in better memory gains than less effortful successful retrieval (i.e., multiple choice question). Roediger, Agarwal, McDaniel, and McDermott (2011), however, discovered that memory gains can occur for multiple choice and free-recall assessments when learners have the opportunity to practice retrieval through repeated testing, which could be readily accommodated in an AR training environment. Augmented reality training solutions should thus consider supporting varied assessments, which would be anticipated to lead to rich memory traces for a wide variety of cognitive processes and knowledge dimensions.

> *ET3 Smith is learning how to identify mechanical issues in an engine room. He first reviews machine and part labels that are typically the cause of mechanical failure. To do this, he dons an AR headset that superimposes the labels (modality: verbal) in spatially accurate locations (modality: spatial) on actual equipment to assist ET3 Smith with the acquisition of this declarative knowledge. As ET3 Smith moves around the engine room, part labels emerge in relation to his spatial location and he is asked to locate by pointing (response: manual) and then verbalizing (response: auditory) each label. This multi-sensory information facilitates the development of a spatial (location) and verbal (part name) working memory traces. For example, the headset prompts ET3 Smith to navigate to the main engine lube oil pump. When ET3 Smith arrives at the pump, the headset will highlight the cylinder lubrication box and ask ET3 Smith to point to and verbalize the label on the*

part. This assessment allows ET3 Smith to elaborate on his verbal and spatial working memory trace, further crystallizing his declarative knowledge about faulty parts.

After passing the part label and location assessment, ET3 Smith loads a tutorial that plays common sounds associated with a mechanical malfunction. After listening to the auditory sounds, ET3 Smith loads an interactive exercise that tethers mechanical sounds (modality: auditory) to a spatial location (modality: spatial) in the engine room. During this interaction, ET3 Smith is tasked with diagnosing the origins of a multi-engine breakdown by seeking out key, spatial-auditory cues by first walking (response: motor) to their location within the engine room and then verbally (response: auditory) articulating the cause of the breakdown. As ET3 Smith approaches the origin of the breakdown, irregular mechanical sounds become more salient within the headset, providing a critical diagnostic cue. The headset also tracks ET3 Smith's spatial positioning to evaluate correct actions within the engine room and give corrective tactile feedback when off course. This interactive assessment allows ET3 Smith to interactively create spatial and verbal working memory traces. Taken together, both exercises maintain strong S-R compatibility, while also allowing for encoding variability (verbal and spatial) that converge at a single knowledge structure (mechanical failure).

SUMMARY

Given the literature on cognitive processes, knowledge dimensions, and encoding processes, AR training and operational support solutions should consider furnishing trainees with stimulus-response compatible solutions that support repeated elaboration and recall within a single memory trace. Further, these solutions should be sensitive to a trainee's proficiency level, with the goal of unfolding more complex content and assessments as trainees deepen their declarative, conceptual, procedural and metacognitive understanding of a domain. A novice trainee who is acquiring information about a system for the first time will benefit from AR content and assessments that convey and measure descriptive knowledge about a system instead of abstract knowledge about a system. In addition, providing real-time feedback and remediation to a novice trainee during the development of lower-level knowledge will produce a strong bedrock of understanding (i.e., both the "how" and "why") as the trainee progresses towards advanced concepts (e.g., Rowland, 2014). In the same manner, more experienced trainees should receive AR content and assessments that are representative of the desired knowledge, skills, and abilities needed to perform context-relevant tasks, while providing opportunities to elaborate on complex ideas and concepts, thereby fostering deeper learning and transfer of training. It is plausible that the pedagogical and design principles reviewed in this paper will provide a framework for developing AR training and operational support solutions that transition trainees and operators out of superficial learning and into deeper understanding of complex domains.

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