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SPECIAL TOPIC ARTICLE

Human-centered intelligent training for emergency responders

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Abstract

Emergency response (ER) workers perform extremely demanding physical and cognitive tasks that can result in serious injuries and loss of life. Human augmentation technologies have the potential to enhance physical and cognitive work-capacities, thereby dramatically transforming the landscape of ER work, reducing injury risk, improving ER, as well as helping attract and retain skilled ER workers. This opportunity has been significantly hindered by the lack of high-quality training for ER workers that effectively integrates innovative and intelligent augmentation solutions. Hence, new ER learning environments are needed that are adaptive, affordable, accessible, and continually available for reskilling the ER workforce as technological capabilities continue to improve. This article presents the research considerations in the design and integration of use-inspired exoskeletons and augmented reality technologies in ER processes and the identification of unique cognitive and motor learning needs of each of these technologies in context-independent and ER-relevant scenarios. We propose a human-centered artificial intelligence (AI) enabled training framework for these technologies in ER. Finally, how these human-centered training requirements for nascent technologies are integrated in an intelligent tutoring system that delivers across tiered access levels, covering the range of virtual, to mixed, to physical reality environments, is discussed.

INTRODUCTION

The COVID-19 pandemic reinforces that emergency response (ER) workers perform extremely demanding tasks in complex, stressful, and hazardous environments associated with critical consequences, including loss of life, serious injury, and significant property damage. These factors are indeed partially responsible for the acute shortage of ER workers (Evarts and Stein 2019). In order to *reduce injury risk and improve ER response, as well as to attract and retain skilled ER workers, there is a pressing need for strategies to improve the training and work conditions of ER workers*. Human augmentation technologies (HATs), such as robots and augmented reality (AR) interfaces, have the potential to dramatically transform the landscape of ER work, and improve the safety, performance, and quality of life of ER workers. Powered exoskeletons, worn by workers, can augment physical capacity and hence potentially deliver machine-like power to workers, while still preserving human autonomy and decision making in unstructured and unpredictable environments. Human-machine interfaces, for example, novel AR interfaces, can be used for the control and operation of ground robots, as well as wayfinding, increased situation awareness, and for improving team collaboration and decision making under stress. Hence, a context-sensitive and use-inspired combination of HATs is likely to tremendously impact both the ER work and worker.

However, despite tremendous potential, existing HAT solutions have been slow to penetrate ER work. In November 2019, our team organized a stakeholder workshop at the *Texas A&M Engineering Extension Service's* Disaster City, where first responders from across domains came together to discuss the opportunities, needs and challenges of integrating augmentation technologies into ER training and field use. From our convergence discussions during this event, we learned that a vital bottleneck has been the lack of high-quality training for ER personnel that effectively integrates training on innovative HAT solutions during emergencies. Hence, new ER training paradigms are needed that are adaptive, affordable, accessible, and continually available for reskilling the ER workforce as technological capabilities continue to improve. The overall vision of our Convergence Accelerator effort is to develop LEARNER – *Learning Environments with Augmentation and Robotics for Next-gen Emergency Responders* – a novel mixed reality learning platform, that accelerates integration of HATs for safer and efficient ER work, supports personalized and adaptive learning sensitive to ER workers' socio-technical opportunities and budgetary constraints, builds and retains skilled ER personnel, and ultimately accelerates next-gen workforce expertise development across different industry domains such as manufacturing and construction.

A COMPETENT EMERGENCY RESPONSE WORKFORCE

Throughout the global pandemic and continuing into the post-COVID19 era, ER agencies have been forced to work with fewer resources to provide an exponential increase in ER services. This, coupled with being in the midst of a digital transformation, indicates that traditional training methods (i.e., face-to-face and text-based online training methods) are inadequate to develop and sustain the ER workforce. To develop a competent ER workforce, trainers must develop critical knowledge, skills and abilities needed for providing life-saving interventions and skilled care in a crisis. However, ER workers also need skills to access, process, and manage large amounts of data, work with emerging assistive and collaborative technologies, and remain capable of making decisions in highly complex, stressful, ill-defined situations. As the digital transformation proceeds and the strain on resources continues, ER agencies will lean more on interventions such as adaptive learning, dynamically adjusting technologies that *adapt* to the learners' abilities and skills (Capuano and Caballé 2020; Abujelala et al. 2021), to develop and maintain their workforce.

Developing a competent ER workforce is a complex and daunting endeavor. ER trainers must develop the knowledge and skills required to provide often life-saving interventions in a crisis and develop decision making skills and abilities for complex, dynamic and unique challenges. As traditional ER training curricula (i.e., face-to-face) are developed, *the trainer is a central part of the development team as he/she guides the content development to ensure it is current and appropriate*. More critically, these training professionals lead the development of the skills and cognitive activities to reinforce the students' learning progression and skills development. As the digital transformation continues and adaptive learning technologies increase, the role of the instructor remains central to the success of ER training. The ER training profession must not only ensure that the content and skills activities are appropriate, but they must also ensure that the context is translated appropriately for each learning intervention. For example, teaching patient handling and lifting techniques with exoskeletons without context may result in good technique, but may fall short of training responders on how to adjust the technique for situations in the field. In other words, teaching ER workers in an environment devoid of context fails to prepare them adequately for the dynamic nature of the work and then fails to build competency.

HUMAN-CENTERED INTELLIGENT TRAINING FRAMEWORK FOR HUMAN AUGMENTATION TECHNOLOGIES

Processes that govern human learning with HATs

Human learning encompasses distinct neurophysiological signatures and cognitive/motor processes that are propelled by bottom-up (stimulus-driven) or top-down (goal-driven) approaches (Wolpert, Diedrichsen, and Flanagan 2011). For the learning process to result in *skilled performance* individuals need to develop expertise across a number of interacting components, including, information extraction, decision making, understanding the classes of control, motor learning, and its representations (Cisek and Kalaska 2010). For for example, during a mass casualty triage event, a responder, equipped with AR tools, should identify victims by urgency, the specific pattern of injury, and if needed – apply a life-saving mode of intervention, all within a short window of time before moving to the next victim or mediating other levels of care. These steps demand high levels of situation awareness, decision making, and motor skills that require feedforward or feedback motor coordination (Wagner and Smith 2008). Unsurprisingly, there are distinct regions of the brain responsible for coordinating these highly asynchronous, and distributed action sequences (Cisek and Kalaska 2010; Tyagi et al. 2021); in fact, unique learning modes are known to govern these skills (Poldrack and Gabrieli 2001). Therefore, the modes of training that facilitate skill learning must be tuned to evoke those responses in simulated situations, while being adapted to the behaviors of each trainee.

Need for adaptive learning

The need for adaptation and personalization in learning originates from a key ideological standpoint – that is, to treat learning as an "experience" that is learner-centered and competency-focused, and not just an "activity" (Mangaroska, Vesin, and Giannakos 2019). This distinction should be made by both the instructors and the trainees, with the expectation being, in its terminus, a "learning experience" will provide a complete learning outcome through some *enabling learning objectives*, whereas an activity points to some level of continuing training demand for expertise development. Several studies have demonstrably shown the individuality of human learning across cognitive (Wilmer et al. 2012) and sensorimotor tasks (Gaunt and Hallam 2009). Unlike some biological phenomena, species-level characterizations or a *one-size fits all* approach to learning remain pedagogical relics that appeal to convenience over effectiveness, and therefore, form the crux of limitations in ER training today.

Human learning is a distributed process, therefore, adaptation and personalization strategies demand cross-platform, multimodal analytics to enable data-driven decisions that augment the learning experience (Mangaroska, Vesin, and Giannakos 2019). These analytics can derive from performance, neurophysiological, and behavioral (PNB) indicators that are collected during an exercise, with adaptations that follow asynchronously or at time-scales relevant to the overall learning activity (Sarrafzadeh et al. 2008). In the past, these methods were encumbered by challenges in the interoperability of data sources or synchronization between frameworks (Blikstein and Worsley 2016). However, with the advent of cross-platform, fully interoperable HATs, particularly AR, virtual reality (VR), and exoskeletons, we have resolved some past obstacles and found newer ones. Data from disparate sources are now easier to collect, yet difficult to interpret, complex to understand, synchronize, and utilize. Furthermore, researchers need to consider the nature of the adaptation, their temporal resolution, and the workload demand these strategies place on the trainee, as adaptation when improperly introduced can have the opposite effect.

Researchers have explored several measures to drive adaptation within intelligent tutoring systems, with varying levels of success. These include time spent on learning environments, interaction data, self-reports, or test performances (Julian and Smith 2019). However, we find that these systems often fail to gather context-aware information from the heterogeneous data-streams, or reliably capture the state of the trainee during the learning exercise. Furthermore, there's a need for these systems to consider user *affect and behavior* that precede oft-used interaction or performance indicators (Normadhi et al. 2019). Data-integration from multiple sources has been successfully shown to improve learning time, retention, and skilled performance using AR, VR, and other multimodal sources (Marienko, Nosenko, and Shyshkina 2020). Therefore, we envision that a similar approach would work reliably for ER training scenarios. Furthermore, there is a need for such systems to be both *proficiency and deficiency-driven*; previous approaches often look at deviations of the trainee from the canonical expert model encoded within the learning system (Asterhan and Dotan 2018), and the subsequent adaptation strategy is centered on trainee deviations from the model or "errors," with no adaptations or support when trainees showed some level of expertise going in. This might be a missed opportunity to overall learning outcomes especially in the ER domain.

Proposed framework

The dimensions of technology-enhanced learning introduced by FitzGerald et al. (2018) aid in explaining our vision for the adaptive learning framework in LEARNER: *What is being personalized?* We wish to personalize training and support for emergency responders during HAT-enabled learning experiences. This personalization will serve individual learning modes and adapt to the requirements of each trainee. *How?* Adaptation and personalization will be driven by PNB markers collected during or prior to the learning exercise and at different time scales contingent on the needs of the learner. *To what benefit?* A data-driven adaptation strategy will quicken the

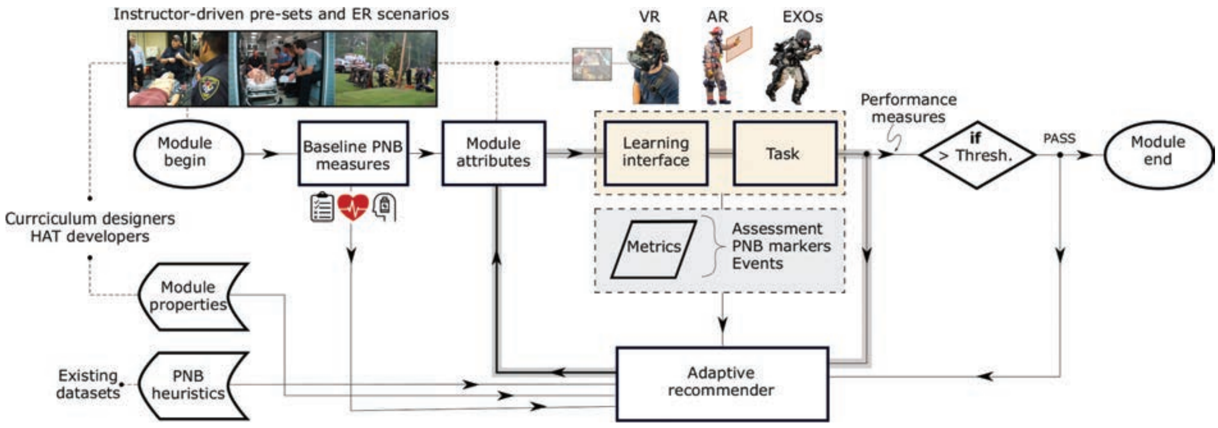

FIGURE 1 Adaptive learning framework for emergency response training

learning rate, improve retention, and the skill levels of the trainees, while offloading some responsibilities from the instructors.

The learning curriculum designed for this exercise embodies a hierarchical structure with modules designed for each HAT entailing distinct learning objectives (activities) that together form the LEARNER's core experience (Figure 1). We envision that this will be technology-agnostic and human-centered, where the individual is actively involved in the loop, and enabled by the changes introduced through the LEARNER system. The framework will operate on three key constructs: *actionable measures, adaptable elements*, and a *guiding strategy*. Actionable measures include PNB markers that are captured during the learning exercise; these can be obtained through wearable sensors (e.g., eye-tracking), self-reports, and/or interaction behaviors. Adaptable elements refer to the elements of the learning experience that can be modified to elicit a change in the trainee's response, reinforce positive actions, or to promote behaviors that counter an observed deficiency. For example, if we note that a trainee's performance is poor in identifying a specific injury type during triage, the system should provide more instances of that injury during iterations of that activity. A guiding strategy ties in with the fundamental premise that drives "learning" on the task which could be observational, error-based, or reinforcement-driven, *this is determined through discussions with instructors on the field and experts on human sensorimotor training*. The strategy can be implemented in a repetition-, change-, or an alteration-centric manner, where the learner is presented with more iterations, a new experience or an altered form of the same experience based on their needs. The nature of the trainee's response will determine the guiding strategy applied or this can be presets as identified by the instructor for each access level.

Given the hierarchical nature, each module entails a finite space of properties, these properties include *trainee attributes* such as role, skills; sensor attributes such as modality, output parameters; *task attributes* such as duration, number of attempts, objectives; *interface attributes* such as elements displayed, saliency of the scene, callouts; and performance attributes such as time on task, task-outcome, etc. We envision that the LEARNER framework will consider individual PNB data in selecting appropriate presets for these parameters at the start of an activity. During the exercise, the module actively processes the PNB data, and determines the need and mode of intervention contingent on the *guiding strategy*. This feature will be mediated by an adaptive recommender system that is fed by both PNB heuristics that we transfer from other related experiments, the user's history across all learning exercises, and user baseline estimates measured before the start of the specific activity. The recommender is then responsible for choosing the appropriate presets for the experience and any modifications in between. This process will continue until the trainee meets the relevant criteria for completion or to move onto subsequent experiences within the training module. Our current approach is geared toward the generation of useful data for each HAT, task-context, and module relevant to the core LEARNER platform. Subsequently, we will explore the transferability of markers and models found relevant in these exercises to the trainees' experience on LEARNER, where *explainability* and computational overhead will help distill our choice of architecture and adaptation workflow.

AUGMENTED REALITY TO ENHANCE TRIAGE OPERATIONS

When designed properly, AR systems can extend users' perceptual and cognitive capabilities by overlaying 2D and 3D graphics onto a users' forward-looking field of view. While not yet this size, we can envision in the near future

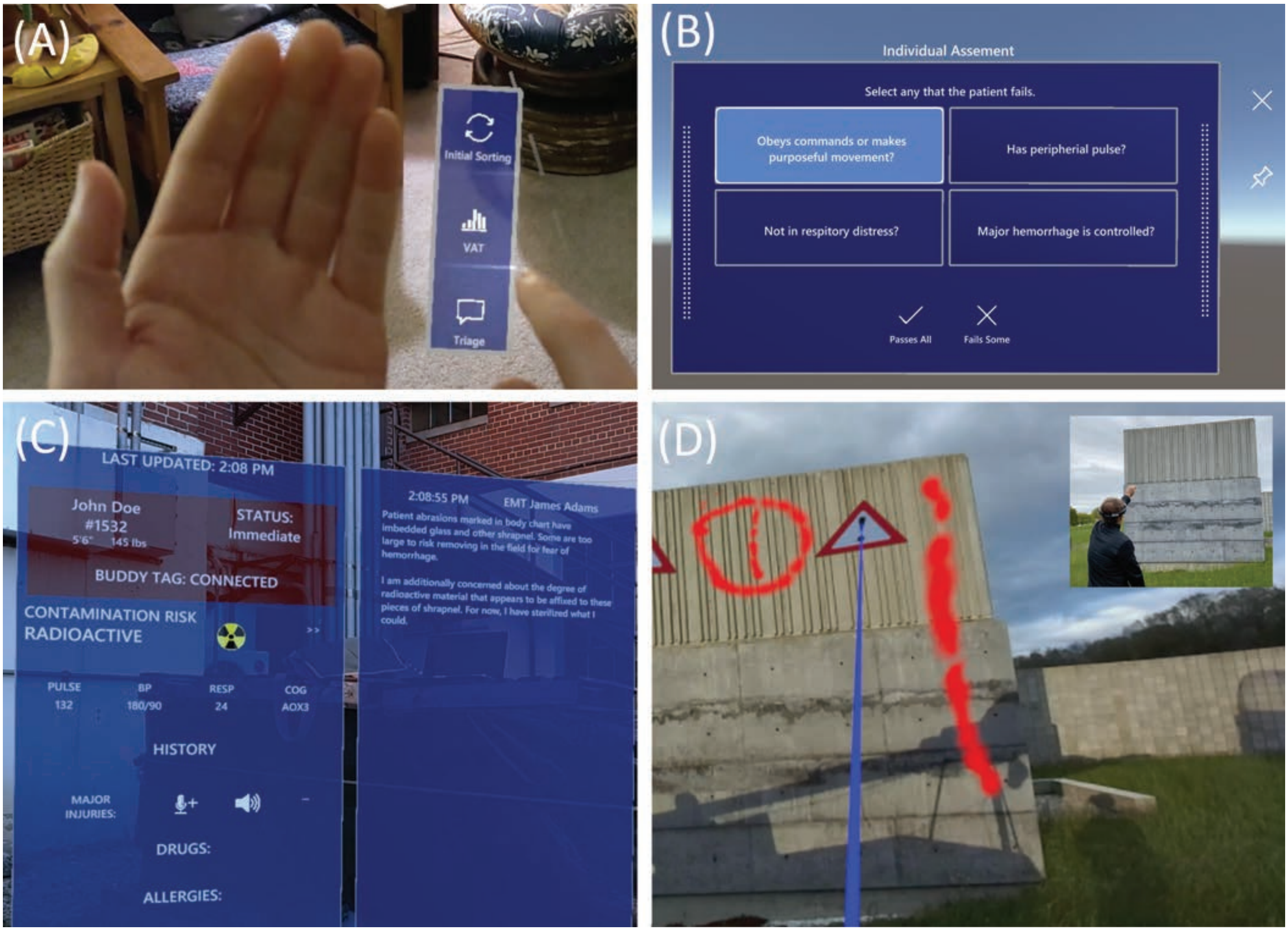

FIGURE 2 LEARNER provides several AR tools for triage in mass casualty events including: (A) hand-relative touch-based menus, (B) SALT virtual assessment tool, (C) virtual triage tag, and (D) scene annotation tools

AR head-worn displays that are as lightweight as glasses and integrated into head- and eye-based personal protective equipment. This soon-to-be-realized vision of AR will immediately transform a number of occupations; moving information currently contained on 2D surfaces that must be held (papers, mobile phones, and tablets) to the users' work environment. And while AR systems are already showing value in military, manufacturing, healthcare, and transportation domains, we have chosen ER in which to field our early LEARNER AR prototypes. AR is particularly well-suited to augment the perceptual and cognitive capabilities of responders by, for example, cueing important hazards in the scene, supporting hands-free access to shared information systems, and allowing responders to virtually annotate to coordinate teams of first responders in large-scale incidents.

LEARNER leverages AR as both an operational human-augmentation technology (i.e., teaching users' how to use AR tools), as well as a learning delivery technology (i.e., leveraging AR to assist in learning how to use other HATs, such as an exoskeleton or unmanned aerial vehicle). This article focuses on the former, where we first developed a set of AR tools to enhance triage during mass casualty events, and subsequently consider how best to train users on these AR tools. Specifically, we employed a *human-centered design process* to identify how best to integrate AR into triage processes and practices, and then iteratively designed and developed a handful of AR tools including aids for Sort, Assess, Lifesaving Interventions, Treatment/Transport (SALT) triage, a virtual triage tag, and AR annotation system. These tools are accessed via a hand-menu that appears when users raise their hand in front of them, palm facing toward them (Figure 2A). All AR-based LEARNER tools support multimodal interaction, in that user interface elements can be selected using a finger poke gesture (for AR graphics within arms' reach, see Figure 2A), a ray cast + pinch gesture (for graphics outside arms' reach), and via voice command (voice prompts are displayed to assist in learning and recall when users glance at a specific AR interface element).

The SALT virtual assessment tool (VAT) presents first responders with a series of questions that effectively walk through a first-contact process of sorting, assessing, performing life-saving interventions, and triage (Figure 2B). These aids can be very useful for experienced first responders in high stress environments as well as provide guidance for new first responders in their first experiences with mass casualty events. The virtual triage tag (Figure 2C) replaces commonly used paper tags, and supports second- and subsequent-contact responses by providing means to electronically document patient name, demographics, injuries, vitals, suspected contamination, allergies, and drugs administered. The virtual triage tag also supports voice-based patient annotations, that can either be played back aurally, or presented via transcribed text (as shown in Figure 2C). The scene annotation tool allows users to place symbology in the scene or use virtual spray paint to mark areas of interest and hazards. As shown in Figure 2D, this tool can be useful in coordinating sorting by augmenting landmarks with custom content.

The LEARNER system leverages AI to adaptively personalize the learning content and learning experiences, including the AR-based learning. However, we envision future AR-based capabilities in the field that leverage AI to create adaptive AR user interfaces. These AR interfaces would move beyond simple personalization or preferences, but instead focus on supporting specific cognitive learning needs, as previously identified, via the adaptive recommender system that is fed by both PNB heuristics, as well as the trainee's historical expertise data. In the current user interface design paradigm, human factor engineers use anthropometry to design for the 95th percentile in hopes that "one size fits all," while HCI practitioners design sets of intuitive and accessible interaction techniques associated with specific devices that must be learned by all users of said devices (e.g., click the left mouse button to select). These approaches then simply map many users to one interaction technique. Using AI, we intend to flip these approaches, and instead of prescribing interaction techniques we will build smart, sensor-based AI systems to drive the user experience that instead over time learn users' preferences and abilities, their tasks, and the environments in order to render an intuitive and effective user experience. Individualized interactions will therefore be personalized and adapt to individual differences of all kinds; physical, cognitive, social, etc. and embolden our unique aptitudes, dispositions, and perspectives. Further, individualized interactions will necessarily include the broader context of ones' tasks and goals at any given time, the setting in which one is interacting, past strategies and preferences when performing similar interactions and so on. These differences can change from moment to moment (e.g., based on transitory levels of stress/arousal) and will also change longitudinally as our abilities change with age and experience. We envision integrating these concepts not only into the operational AR user interfaces but also the LEARNER learning experience.

VR-BASED EXOSKELETON TRAINING FOR PATIENT HANDLING

Assistive devices, such as exoskeletons, have shown great potential to augment human physical capabilities and reduce injury risk in responders during physically strenuous missions such as patient/victim handling. With an increase in the development and adoption of exoskeletons, the need for training platforms that can quickly adapt to varying device designs is vitally important. Since motor skills training plays an important role across a wide range of occupational and rehabilitation fields (Holden 2005), we propose a VR-based training framework. The proposed framework incorporates biomechanical modeling, multimodal feedback, and online task evaluation, while aiming to train users on the use, benefits, and limitations of exoskeletons. To assess the effectiveness of training, trainee motion will be measured in VR and assessed via musculoskeletal modeling methods. To facilitate VR-based exoskeleton training, we propose a training framework that integrates multiple feedback modalities, including visual, vibrotactile, and force-feedback, that can simulate various parameters of exoskeleton operation.

The proposed training framework follows the schematic illustrated in Figure 3, which captures two modes of training ("offline" and "online"). The starting point for both modes (Box 1) is the creation of a motion and modeling data library, that comprises a range of expert data collected on a variety of tasks, as inputs to a musculoskeletal model. Data will be collected to represent a broad range of human (e.g., anthropometry) and task characteristics, and will be incorporated into simulation-based musculoskeletal modeling tools to enable the synthesis and analysis of motion paths and characteristic values. Possible combinations of the synthesized motion data and a variety of exoskeleton parameters are inputs to musculoskeletal modeling tools, to create a library of input–output relations that estimate body-joint torques and metabolic outcomes for a given set of inputs (i.e., human task, exoskeleton characteristics).

In both training modes, the trainee is immersed in a virtual presentation of a task to perform and can "choose" exoskeleton parameters for performing such a task. Exoskeleton parameters of choice include shoulder/back device, assistance level, and specific passive/powered torque profiles. Once the trainee makes the choice, they perform the task presented in VR, and their body motion

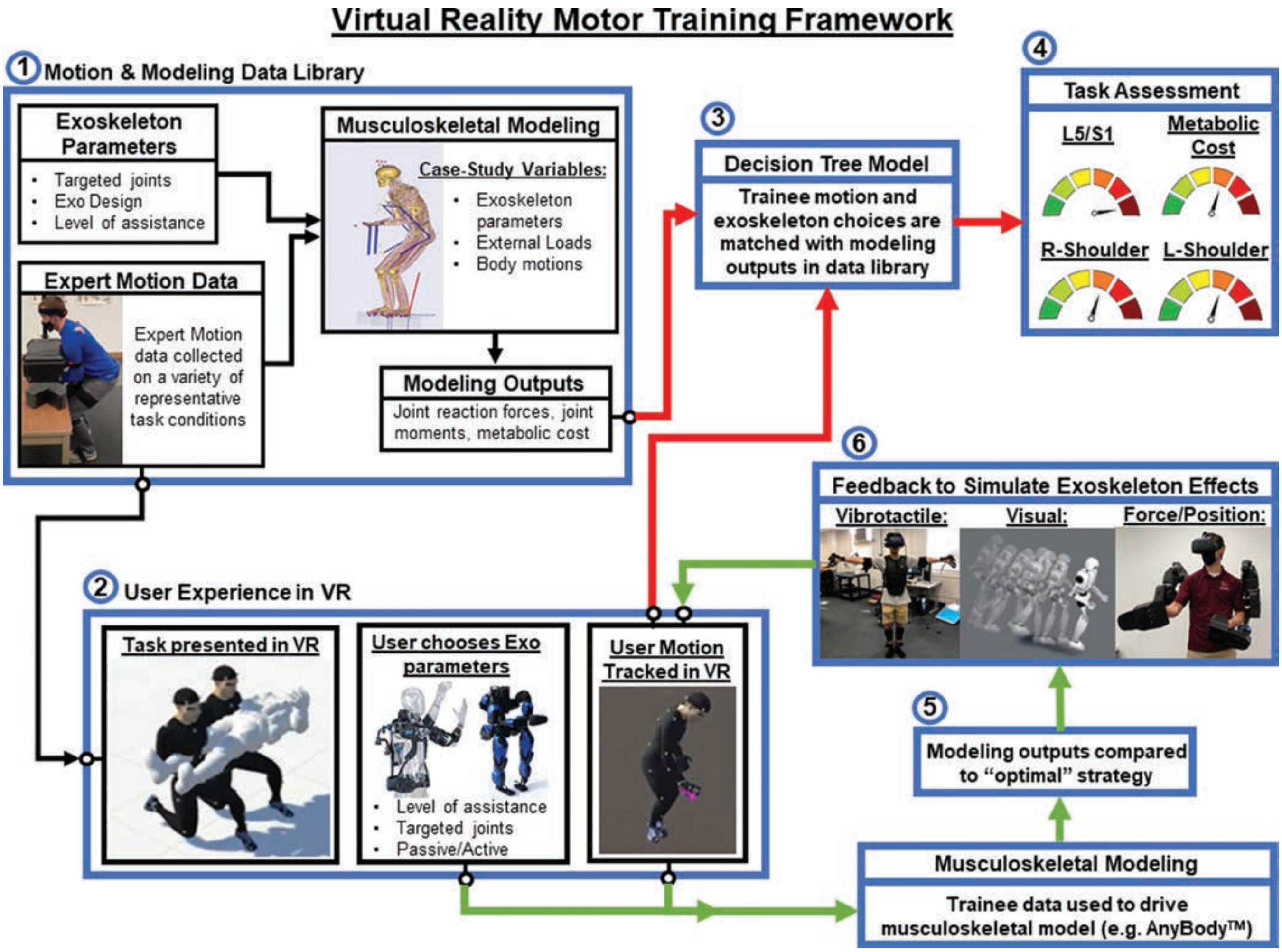

FIGURE 3 Virtual reality-based motor training framework for the use of exoskeletons

is tracked (see Box 2). The red arrows show the flow of logic for "offline" model-based training (Boxes 1-2-3-4). In this mode, the tracked motion of the trainee and their exoskeleton choices are matched with relevant inputs in our modeling library, and the corresponding musculoskeletal and metabolic outputs are selected from the modeling library. These results are presented to the trainee as an info-graphic (Box 4). The green arrows show the additional flow of logic for "online" model-based training (1-2-5-6): In this mode, the trainee "experiences" the exoskeleton not only visually, but also through vibrotactile or force-feedback modes. In addition, the trainee also receives real-time, multimodal feedback to help improve their movement strategies, through guided trajectories. In the force-feedback mode, a robotic device simulates physical interactions by providing a *least-resistance path* for trainees to follow. The target strategies pathways can be generated to either mimic expert exoskeleton users, or through optimization outputs from the modeling software, based on human body-joint loading.

THE LEARNER ARCHITECTURE

The LEARNER platform (Figure 4) is built on top of Generalized Intelligent Framework for Tutoring (GIFT; Sottilare et al. 2017), which makes it open, modular, and distributed/cloud enabled. The LEARNER architecture includes domain knowledge plug-ins/modules which provide the training content builder with the constructs for training in a specific domain. Training content is stored in a common content format (represented partially in SCORM/xAPI) for utilization by the training configuration manager during the execution of training events. Training delivery plug-ins/modules convert training content to specific training delivery environments (e.g., web-based, AR/VR/MR, haptic suit) and send back trainee actions as the training executes. The LEARNER architecture supports both performance-based and state-based (using PNB measurements) evaluation, which also enables both macro- and microadaptation in order to optimize training effectiveness. The LEARNER platform supports

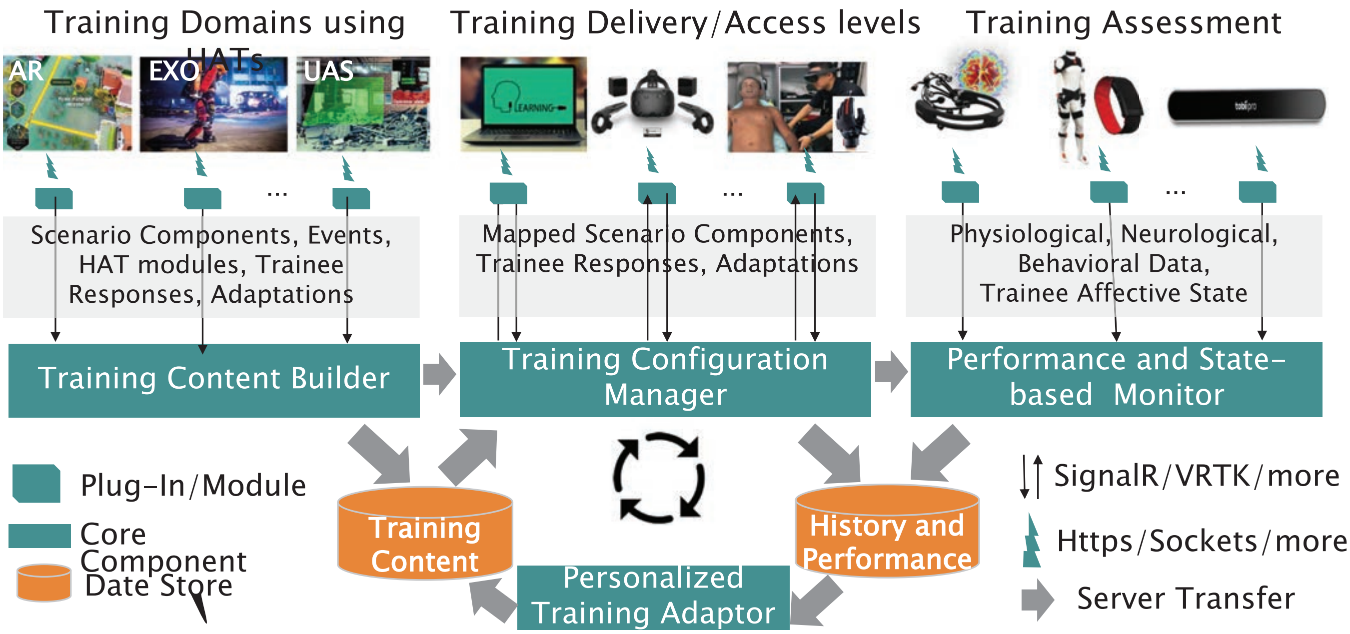

FIGURE 4 LEARNER Architecture

multiple accessibility levels to serve the training needs of the future ER workforce be it from home, to modest rural ER facilities, to large metropolitan operations. Instructors and trainees can login to the system and interact with the various core components. The *Training Content Builder* provides training instructors/creators with the ability to both define domain knowledge plug-ins as well as build training content (using the plug-ins). The *Training Configuration Manager* allows trainees to access and execute training content as well as deliver training content, capture response information from the training delivery plug-ins, and orchestrate the use of PNB data collection devices. The *Performance and State-based Monitor* initializes PNB device use and captures data using PNB plug-ins. Finally, the *Personalized Training Adaptor* includes algorithms that analyze trainee data during and after training to dynamically update content for personalized training. Trainers/instructors can access training and performance data across all trainees to gain insights into training progress, performance trends, and specific user results.

CONCLUSION

There is little question of the importance of having a well-developed, capable, and competent workforce, especially when the workers respond to dangerous, ill-defined situations in which human life hangs in the balance. Developing this workforce often requires a transdisciplinary team to develop and implement effective training. Yet, we are in the midst of great changes in the workplace. Some changes have been induced by global events, such as the COVID19 pandemic, that result in fundamental changes to the workers' performance requirements (i.e., increased outputs with fewer resources). Other changes are brought on by the evolution and implementation of emerging and innovative technologies intended to improve human performance. Developing the workforce to adopt and accept technologies, such as exoskeletons, AR/VR, and AI, to work effectively and efficiently in the transformed workplace will require innovation. Designing, developing, implementing, and evaluating these development *experiences* for this continually transforming workplace requires a new paradigm and new tools, processes, knowledge, and skills to meet the demands of the current and future workforce. Throughout this article, we have provided a glimpse of *LEARNER* to describe what human-centered efforts may be required to meet the needs of training ER workers in the use of nascent human augmentation technologies. Our transdisciplinary approach converges and enhances the existing knowledge from the disciplines of learning science, computer science, AR/VR, human factors, cognitive psychology, and systems engineering to create the LEARNER platform that integrates training course design, innovative and emerging technology implementation, and new techniques of work.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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