# A generic framework of intelligent adaptive learning systems: from learning effectiveness to training transfer

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Abstract

To provide guidance for adaptive learning systems designers, this paper reviews evolution of learning theories and their associated progress, which is eenabled by computers, artificial intelligence, and augmented cognition. A generic conceptual framework, of intelligent adaptive learning systems is discussed in detail for individualized learning. The utility of such design methodologies is illustrated through an example of a customized intelligent tutoring system for IED disposal operator training. This testbed approach is the first phase of truly determining the utility and effectiveness of intelligent adaptive learning systems for multiple fields of use in the ever complicated spectrum of society's education and training needs.

**Keywords: adaptive learning; intelligent tutoring; individualized learning; customized training; intelligent adaptive learning system; learning effectiveness; training transfer**

## 1. Introduction

Training in many fields has become complicated due to dynamically changing task environments and the introduction of new technologies. Developing advanced technology solutions for training is especially needed for the military where training systems are transitioning from dedicated trainers to flexible multiuse workstations (Osaga, 2000). This transition makes presenting learning material across varying occupations a challenge (Nicholson et al., 2006). Given the complexity of the training requirements and associated constraints in the field, what human-machine interaction design principles should training designers and systems developers to leverage and build more effective adaptive learning technologies?

This common, yet critical question faces many training system project authorities and designers in their day-to-day jobs. Answering this question is not easy, as many different adaptive learning theories and associated design methodologies are available in various application domains. It is even more difficult when considering the advance of technologies such as artificial intelligence (AI), Big Data, cloud-based computing, and social media, etc. Especially for military training, which is the focus of this paper, the issue is how to transfer learning efficacy shown in adaptive training simulators to learning effectiveness for field applications.

To address the lack of guidance for transferring learning effectiveness to field training when designing adaptive learning systems, this paper reviews the progress of evolving adaptive learning technologies and proposes a generic conceptual framework and associated adaptation strategies for intelligent adaptive learning systems. The aim is to provide tools and guidance for training system designers when designing adaptive learning systems with the focus of intelligent adaptation. The remainder of the paper is organized as follows. Section 2 gives an evolutional review of adaptive learning systems which leads to a definition of intelligent adaptive learning systems. Section 3 explains the motivation of augmented cognition-based intelligent tutoring systems (ITSs) for military training. Section 4 describes a generic conceptual framework of intelligent adaptive learning systems and its components. Section 5 presents an example of such intelligent adaptive learning systems. Section 6 provides concluding remarks.

## 2. Evolution of Intelligent Adaptive Learning Systems

This section is not an exhaustive historical review of all learning systems. Instead, it highlights the integrated components that guide changes in learning systems and their design elements namely: learning theory which drives learning requirements, instructional design principles which interpret learning requirements, and the delivery platform which communicates the learning concepts to the learner. The integration of learning system components is first illustrated with "teaching machines" that facilitated individualized learning through operant conditioning in classroom and training environments (Skinner, 1958).

Operant conditioning sought to strengthen the association between the stimulus (i.e., the learning material) and the response (i.e., the correct answer) as the mechanism of learning. The instructional design aspects of this learning theory included 1) real-time feedback to the learners' response, 2) alternative questioning for incorrect responding, and 3) learner controlled pace (Skinner, 1958). Teaching machines as a delivery system allowed for customized instruction in an anytime, anywhere fashion. However, the learning theory ignored the importance of the prior knowledge of the learner and did not consider individual differences in motivation or current health status of the learner

The 1970's and 1980's experienced advancements in cognitive theories pertaining to how the brain learns and how technologies such as the computer and AI assisted in facilitating the learning process. These breakthroughs made possible adaptive computer-aided instruction (CAI) systems or tutors that continued to individualize learning (Carbonell, 1970; Sleeman & Brown, 1982). It was Wenger (1987) who applied an interdisciplinary approach in combining learning theory (e.g., experiential learning) with instructional design in an intelligent computer-aided instruction (ICAI) platform that allowed the student to interact dynamically with the learning material in a manner that facilitated higher order concept formation or domain expertise.

Wenger's ICAI model consisted of four components: 1) domain knowledge, 2) user interface, 3) communication strategies, and 4) student model. Domain knowledge represented the source of learning material that could be captured and maintained in a database. The interface was integral to appropriately delivering the learning material to the learner as it conveyed how the user would interact with the system and how feedback during and after responding would occur. Communication strategies included automated decisions about when and what material is displayed. The student model represented his/her current state knowledge and emotion. For the first time, these strategies accounted for the student's performance, motivational, and emotional levels. Further, mitigations or intervention strategies provided a means to keep the student in the optimal state of learning throughout the instructional time course.

The learning system used the student state information as a diagnostic to formulate and update the student model with data captured during his/her interaction with the ICAI. These diagnoses guided the adaptation process to choose the course of action that matched the student's current knowledge state. The improved flexibility of these designs supported the successful transition of some adaptive systems into classrooms and workplaces (Anderson, et. al., 1995; Parasuraman et. al., 1992).

The ITS is an extension of ICAI and shares the characteristic features of Wenger's model (Fletcher, 1985). In addition, an ITS aims to automate some of the supervision, facilitation, and feedback required for self-paced learning (Sleeman & Brown, 1982; VanLehn, 2006). Kulik & Fletcher (2015) noted the difficulty in operationalizing components that define current learning system as an ITS as they defined an ITS when performing their learning effectiveness meta-analysis. Kulik & Fletcher used criteria that included the common ITS definition with the additional caveat that the computer should tutor like a "human tutor" by providing assistance throughout problem solving (p. 7). Using this inclusive definition, the researchers found that using an ITS as a learning platform raised test scores .66 standard deviations above conventional levels or raised a learners performance from the 50$^{th}$ to 75$^{th}$ percentile.

While this learning effectiveness measurement is impressive, it uses a different measure of pre and post testing to compare across test scores. This metric does not address the complexity of adaptive training simulators for military training nor does it address how to measure learning effectiveness for transferring training to the dynamically changing task environment of the Soldier. The effectiveness measure for an ITS in a military context is one of learner mastery rather than tutor effectiveness. Thus, the goal of the adaptive ITS for military applications is to train the Soldier effectively and efficiently with a level of subject matter mastery that facilitates transfer of training (Hou and Fidopiastis, 2014). In other words, training systems need to be both adaptive and intelligent to meet learning requirements while facing the application constraints. An intelligent adaptive learning system should be intelligent enough to dynamically adapt the learning content to fit individual, real-time learning needs so that optimal learner states (e.g., engagement, performance, workload, arousal, etc.) are attained and maintained and the entire learning experience is optimized.

## 3. Augmented Cognition Motivating ITS for Military Training

The field of Augmented Cognition (AugCog) theorizes that a military ITS combined with psychophysiological state detectors will improve the effectiveness of learning and may even accelerate it due to its extensibility into team-based training (Palmer & Kobus, 2007). AugCog-based ITSs differ mainly in the capability of the learning system to adapt to the learner (Schmorrow and Kruse, 2004). As such the learning system becomes a closed-loop design with the learner driving the learning process. The ultimate goal is a collaborative relationship where the human and learning system cooperatively derive solutions to the operational problem space. The AugCog concept changes the role of the ITS from a tool to a partner in imparting and generating new military relevant knowledge.

The adaptive instructional architecture (AIA: Nicholson et. al, 2007) was one such AugCog ITS model designed to incorporate cognitive state metrics derived from psychophysiological sensors for military training. The AIA approach merged the constructs of experiential learning, cognitive load, and adaptive systems into a military relevant testbed simulation capable of measuring multimodal psychophysical responses of the learner. A multimodal sensor approach derives the learners' cognitive state using a convergent method of multimodal data assessment for accurately identifying the cognitive construct (e.g., using multi-sensors to assess high arousal states).

St. John, Kobus, & Morrison, (2003) showed that single sensor psychometric data (e.g., heart rate) had up to a 40 percent accuracy in identifying the cognitive construct (e.g., cognitive workload) monitored by the ITS. Multimodal data classification increased the predictive capability of the ITS to between 70 and 98 percent. Given the need for multimodal sensor fusion capabilities, the AIA system incorporated a signal-processing block that synchronized, feature extracted, and classified the fused biosensor data to improve the accuracy in predicting the learner's engagement, arousal, and workload.

More importantly, the AIA is an example of a closed-loop AugCog-based ITS testbed. The testbed approach allows for the evaluation of learning theories, instructional design implementations, sensor technologies, and diagnosis/mitigation strategies individually or combined (Sciarini & Nicholson, 2009). For example, Karamouzis & Vrettos (2007) introduced a behavioural cybernetics ITS approach similar to the information processing approach of AugCog. Within a cybernetics framework, motor processing modified through sensory feedback underlies all behaviour (Smith, Henning, and Smith, 1994). Thus, the AugCog ITS interface would lack the ability to appropriately transfer control between the ITS and the learner (Fidopiastis, 2014). The AIA potentially represents a generalized framework from which to assess the most effective strategies for optimizing training and accelerating learning.

Fuchs et al., (2011) do caution that laboratory-based testbeds may not provide field deployable training solutions. Thus, the value in the testbed approach is in determining viable components of the ITS as part of the initial development cycle. The key is that transferring the simulation based efficacy to the actual training effectiveness requires sensors and associated algorithms integrated within the real world context (Hou & Fidopiastis, 2014). Three main design issues still faced are: 1) defining metrics derived from the multimodal data streams that reliably predict the learner's cognitive state, 2) determining the relationship of the metric and that of mitigation selection, 3) developing metrics to assess the construct validity of the ITS and the learning transfer to the operational environment. To address these issues, a generic intelligent adaptive learning system framework is needed to guide training systems design, evaluation, and determination of system viable utilities for exploitation.

## 4.~~A conceptual framework of intelligent adaptive learning systems~~

From the review of the main components of adaptive learning technologies including both CAI and ICAI systems, and ITSs discussed above, a number of fundamental characteristics can be extracted for intelligent adaptive learning systems:

- Tracking learner goals, plans, or intents, and progress made towards them;
- Monitoring and inferring the internal state of the learner (e.g., cognitive, emotional, physical, behavioural, etc.);
- Monitoring and inferring the external state of the learning environment (e.g., other entities, environmental conditions, domain knowledge, etc.);
- Monitoring the effects of learning system status, advice, and adaptation on learner and environment state (i.e., closed-loop feedback); and
- A customized user interface to handle the interaction/communication between the learner and the learning system.

Figure 1 is a generic intelligent adaptive learning system framework which was adapted from Hou, Banbury, & Burns (2015) based on human-machine interaction principles. It includes functional modules pertaining to learning situation and learner state assessment, an adaptation engine, and a user interface. The models that support each of these modules are expert model, task model, system model, world model, learner model, and interaction model, which are also included in this Figure. The four functional modules are common but critical to all intelligent adaptive learning systems. Each module is described below to enable learning systems designers to gain a high-level technical understanding of the scope and capabilities of each of the modules and how they interact with one another.

### *4.1 Learning situation assessment*

The learning situation assessment module is concerned with assessment of the learning experience or the "situation". It comprises functionality relating to real-time analysis of the task (i.e., the sequence of activities needed to achieve a specific goal or learning objective) and decision support on most suitable learning contents, format, modality, and pace, etc. A learning situation assessment module monitors and tracks the current progress towards specific learning objectives through knowledge of the learning plans, activities and tasks, and the learning system itself. Using this knowledge, the module is able to assist the learner through decision support or by adapting what learning material is presented to the learner.

Underpinning this module is an expert model. The purpose of the expert model is to represent the knowledge, skills, or behaviours that embody the desired state of the learner within the context of a specific learning activity. The contents of the expert model are task–specific and remain static during task execution—the learner's interaction with the system does not alter the representation of knowledge, skills, or behaviours. The expert model encapsulates three aspects or models of representation:

- The expert model must represent required learner proficiency within the specifics of the learning activities. In other words, the 'what' that the learner must do to in order to successfully complete the learning task (i.e., task model: Hou et al., 2011);

- The expert model must represent expert behaviours and skills—the ‘how’ that is used by the system to provide feedback and assistance to the learner in the form of advice or support (i.e., system model: Hou et al., 2011); and
- The expert model must represent the external world in terms of the entities that exist in the environment, their properties, and the rules that govern them (i.e., world model: Hou et al., 2011).

The expert model is also used by the adaptation engine to assess the learner’s state of competency during learning. A learner model is compared to the expert model to assess the nature of the learner’s current deficiency, to drive the adaptation process, and to provide support and assistance to the learner.

### *4.2 Learner state assessment*

The learner state assessment module comprises functionality relating to real-time analysis of the psychological, physiological and/or behavioural state of the learner, as well as the environmental context that the learner is working within. The primary functions of this module can include continuous monitoring of workload, inferences about current attentional focus, ongoing cognition (e.g., visual and verbal processing load) and intentions, using extensive a priori learner knowledge (e.g., models of human cognition, control abilities, and communication). Overall, this module provides information about the objective and subjective (i.e., internal) state of the learner within the context of a specific learning activity. This information is used to optimize the learning experience as it provides the basis for intelligently adapting the learning content to match the needs of the learner.

Underpinning this component is a learner model (same as the ICAI student model as discussed in section 2). The purpose of the learner model is to represent the current knowledge, skills, or behaviours that embody a specific learner performing a specific task based on models of human cognition, control abilities, and communication. The contents of the learner model are both task and learner specific, and they evolve dynamically during the execution of the learning task. In other words, the learner's interactions with the learning system update the modelled state of the learner's performance and competence. The learner model is used by the adaptation engine to compare the current learner model with the expert model to assess the learner's deficiencies. This information is used to drive the adaptation of learner assistance and support to enhance and mitigate human information processing capabilities and limitations.

The learner model can be segregated into information directly related to the learning activity and information that is more general and unrelated to the task. The learning-related information would have the same composition as the expert model, but would contain an assessment of current learner state rather than desired learner state. The information considered more general and unrelated to the learning activity would include knowledge about cognitive abilities, learner preferences, and training background. This aspect of the learner model can also be populated, where possible, with historical information about the learner such as training received, previous task performance assessments, etc.

The learner model can also be updated dynamically during the performance of the learning activity. In this case, the learner's interaction with the learning system and the learner's performance can be used to update the task-related aspects of the learner model. The learner state assessment module must therefore be able to use learner state measurements (e.g., eye tracking, psychophysiological data, and learner behaviour and subjective self-assessments) and contextual measurements (e.g., ambient conditions and learning system status) to make assessments of high-level learner state (e.g., workload, stress, arousal, performance, proficiency) and update the learner model accordingly.

### *4.3 Adaptation engine*

The adaptation engine uses the higher-order outputs from the learner state assessment and learning situation assessment modules. The goal is to maximize the fit between the learner state provided by the learner state assessment module to the learning system status and learning situational assessments provided by the learning situation assessment module. These integrative functions require that the adaptation engine module is able to influence prioritization and allocations of the learning content and/or determine the means by which the information is presented to the learner so that the content dynamically adapts to fit individual real-time learning needs (i.e., intelligent adaptation). For example, the adaptation engine module can offer a range of authority between adaptive systems (i.e., system-initiated adaptation) and adaptable systems (i.e., learner-initiated adaptation). In other cases, the adaptation engine module can also provide advice to the learner (e.g., suggesting how to accomplish a specific learning task that the learner is having difficulty with) or adapt the information available for presentation (e.g., reducing the amount of learning material presented to the learner by presenting only critical learning content during periods of excessively high workload levels).

Figure 2 illustrates the three functional components that comprise the adaptation module:

- Adaptation assessment component – This component is responsible for producing system-initiated adaptation demands by comparing the learner model and the expert model. Some adaptation aspects might depend only on the learner model. For example, workload is one factor that influences adaptation that depends only on the learner model. Other adaptation demands are based on the differences between the learner model and the expert model. For example, learning performance is assessed by a comparison of the learner's actual performance to hypothetical expert performance and performance standards captured in the expert model.
- Learner control component – This component is responsible for handling learner-initiated adaptation demands (i.e., learner input). For example, during a learning activity the learner might produce adaptation demands through the interface. The learner control component coordinates learner demands received through the interface to the adaptation engine.
- Adaptation engine – This component is responsible for both the translation of system- and learner-initiated adaptation demands into changes in the learning material presented to the learner through the interface and the level of system support that can be given to the learner. The adaptation engine considers the adaptation demands, the available learning content that can be presented to the learner (e.g., content parameters, adaptation status, and system-generated advice), and the range of adaptations possible (e.g., learning material presentation options or levels of adaptation). From this, the adaptation engine module controls the interface in its delivery of the adapted content or support and presents relevant learning material to the learner accordingly (i.e., interaction model in Figure 1, Hou et al., 2011). Based on the characteristics of

the learning content, this adaptation could either be continuous during the execution of a learning task, or there could be a dynamic alteration of the sequence of learning objectives that are presented to the learner.

### *4.4 User interface*

The interface is the means by which the learner interacts with the learning system in order to meet the learning objectives. There are many ways a learner can interact with the system through the interface: keyboard, mouse, headset with microphone, web camera, and display monitor. Other input devices, such as joysticks, game controllers, and even smart phones can also be considered. The design of the interface is defined by existing Human Factors best-practice and standards.

All four modules operate within the context of a closed-loop system insofar as there is a feedback loop that re-samples learner state and learning situation assessment following the adaptation of the interface. The goal is to dynamically adapt the learning content to fit individual, real-time learning needs so that optimal learner states (e.g., engagement, performance, workload, arousal, etc.) are attained and maintained and the entire learning experience is optimized.

## 5. An example of intelligent adaptive learning systems: QuestionIT

To illustrate how the framework of intelligent adaptive learning systems is applied into real world training design, this section describes a working example of such a system: the intelligent tutor for questioning technique (QuestionIT). QuestionIT was the result of an applied research project led by Defence Research and Development Canada (DRDC). The goal of this project was to develop a domain specific trainer to provide capabilities and attain a high level of effectiveness in Improvised Explosive

Device Disposal (IEDD) operator training. Specifically, it addresses 1) the training of questioning strategy to 2) improve questioning efficiency for 3) IEDD operators' questioning and interview skills when they are at the scene and under temporal pressure to assess the situation.

### *5.1 IEDD course*

The IEDD course aims to train operators to gather, assimilate, and analyse important information to establish the device type, plan, and conduct Render Safe Procedures (RSPs) in accordance with IED principles and best practice. Questioning technique (QT) is the cornerstone of IEDD operations because it enables the IEDD operator to determine and apply the appropriate RSPs to the IED. However, effective questioning of the witness by the IEDD operator to discover key clues about the type of IED is both one of the most critical aspects of the IEDD operator`s role and one of the most difficult skills to train.

Despite the IEDD course content describing specific lists of device-related questions, instructors reported that the actual skill involved in good QT could not be taught because there was no "one-right-way" to question a witness; how students reached that conclusion is for them to figure out. Furthermore, instructors reported that the few who were immediately successful were "naturals"; while the rest of the students managed to pick it up after multiple practice scenarios. The remaining students who do not learn how to conduct effective questioning will, more than likely, end up failing the course.

Effective questioning is difficult because of the amount of information that must be compiled in this training. The students are taught in theory that information elements extracted from the witnesses and the environment (i.e., clues) are entered into the appropriate device column in their check-list table. Towards the end of the interview, the device with the most evidence should indicate the highest probable threat. This technique works so long as the information inputted into the table is accurate. Accurate information stems from asking the right questions. The answers then must be amalgamated with different sources, including visual cues from the scene itself, auditory and short term memory from the witness and other personnel questioning, all within the scope of trained procedure recalled from long-term memory. While an experienced operator may be able to filter this complexity of data into the key elements and their relations, this is undoubtedly a huge amount of information for the novice students to handle. As a result, students can become overwhelmed with the amount of information available and tend to fixate on the immediate, surface level details of physical device characteristics.

### *5.2 QuestionIT design process*

To address the training issues and improve the course success rate of 60% (Hou et al., 2010), the ITS technology was chosen to be developed and integrated within the Canadian Forces (CF) IEDD operator training course. The design of such ITS technology followed the generic conceptual framework of intelligent adaptive learning system as discussed in Section 4 and started with a stakeholder analysis and cognitive task analysis (CTA). The stakeholder analysis resulted in a list of requirements, training methods, typical training scenarios, instructional content, etc. from the IEDD training. CTA process decomposed two training scenarios into course component parts from scenario to IED elements, and then to witness knowledge, and so on. These outputs were used to populate various models (i.e., expert model and student model) of the intelligent adaptive learning system framework and develop instructional content. These outputs helped the process that the tasks involved in training are matched to motor, cognitive, perceptual, and multi-modal aspects of the training needs.

A thorough literature review was also conducted to survey and synthesize the body of knowledge of QT uses in the police, medical, psychology, and professional domains. Accordingly recommendations and best practices regarding how to integrate this knowledge into both the instructional content and assessment of student QT skills were developed (Hou et al., 2010).

CF IED Subject Matter Experts (SMEs) provided guidance on the scenarios that implemented the stakeholder requirements. These requirements included: 1) individual and self-paced training, 2) challenging, yet equivalent context relevant scenarios depicting different types of IEDs, and 3) characters should include witnesses and the On Scene Commander. The initial test scenarios took place in a university psychology department, on an office floor and in the parking garage respectively. Verbal and visual cues embedded in the scenario allowed for classification of three types of IEDs: command (bomber chooses initiation time), timed (pre-set delay), and victim (luring device). Other parameters defining IED type are bomber tactics and characteristics of the target.

A decision tree approach provided a means to evaluate the exactness of the QT of the trainee. Scenarios matched on number of cues and the number and type of question (good, bad, neutral). These question trees were then exported to XML files for quick upload to the QuestionIT. The QuestionIT provided feedback on whether the question was good or poor. Based on cues and questioning, a virtual instructor (i.e., intelligent tutor) provides a report on the trainees overall performance.

### *5.3 QuestionIT adaptation and student state monitoring*

With the understanding of how adaptation module works for intelligent adaptive learning systems discussed in Section 4, a hybrid approach of combining four adaptation mechanisms was suggested for QuestionIT. The idea was that the instructional intervention of the intelligent tutor could be adapted to the learning needs and experience of the student. The four mechanisms are attention tracking, cognitive learning styles, performance tracking, and student state tracking. Due to the limited time, the maturity of the technology and the constraints of the IEDD course during the development of QuestionIT, the suggested four adaptation strategies were not all taken. Only performance tracking was implemented into QuestionIT as an adaptation mechanism. The rational for the inclusion or exclusion of the adaptation mechanisms is summarized as follows:

- Attention tracking. This mechanism uses gaze information to infer knowledge of visual clues when inspecting the suspect device. Eye Tracking was partially implemented using cursor-based tracking; however, this functionality was removed from the final version of QuestionIT as it was considered unrealistic to allow students to visually inspect the device while questioning the witnesses. Eye tracking to assess how students consider questions has been planned for further investigation in a lab environment;
- Cognitive learning styles. This mechanism adapts training content to the learning style of students (e.g., text vs. pictures). Learning styles were not implemented as the earlier baseline study of IEDD student learning styles demonstrated that this population had a very homogeneous sample (i.e., predominantly visual-based learners). However, this knowledge of the dominant

learning style of IEDD students was used to develop the training materials presented by QuestionIT;

- Performance tracking. This mechanism adapts training content to questioning and threat evaluation performance. Performance tracking was implemented to provide both real-time feedback of questioning and threat assessment, and customised training modules on completion of the training; and
- Student state tracking. This mechanism uses an ‘affective response’, measured using Heart Rate Variability (HRV) and Electrodermal Response (EDR) to infer the discovery of clues when inspecting the device and questioning witnesses. This psychophysiological state tracking was not implemented due to a combination of technical difficulty and logistical challenges associated with implementing these technologies, unsupervised, at the IEDD training school. Psychophysiological state tracking using HRV to track students’ affective arousal during witness questioning is currently being planned for further experimental investigation. This measure can be used to infer overall levels of stress, and trainees’ affective level of arousal in reaction to presented stimuli.

### *5.4 QuestionIT implementation*

QuestionIT implements instructional contents into a training scenario. The scenario requires students to question a number of witnesses in order to reveal and identify clues that support or refute command , timed, or victim IED types. The instructional contents are specific lines of questions taught in the IEDD course which are designed to determine the situation awareness (SA) elements about the IED. The questions are designed to facilitate building witness rapport, question specificity (e.g., open, closed), and active listening strategy. A Rapport, Alternative 5Ws, and Re-Evaluation (RARE) framework is used to merge instructional design theory and practice of IEDD QTs by facilitating the process of the bigger picture first before becoming focused on specifics, followed by double-checking one's assumptions before making a final decision. The alternative 5Ws are "who, what, when, where, and why" type of questions based on specific lines of questioning about the IED which are taught in the IEDD course.

By comparing student performance (based on current and past question selection) against a rule set of right questioning techniques, the intelligent tutor generates evaluation comments as real-time feedback on question selection/sequence and IED clue classification to improve student questioning efficiency and decision making skills on identifying factors about the presence and types of IEDs. By adopting the conceptual framework of intelligent adaptive learning systems discussed in Section 4, the main software components of QuestionIT include a graphical user interface (GUI), an evaluation engine, and an adaptation engine, as illustrated in Figure 3. The evaluation engine compares student performance based on current and past question selection and updates the student model with the student's current state of learning. Then, the adaptation engine compares current student performance (i.e., student model) with the desired student performance (i.e., expert model), and selects the appropriate instructional content which appears to the GUI through the training delivery module as intelligent tutor's feedback. The instructor module was not implemented as it was decided by the IEDD course instructors that QuestionIT should be a completely independent learning experience for the student.

The feedback within QuestionIT is interactive for user control by which students have the ability to select or ignore the pop-up feedback window. These instructional interventions can be provided in audio, image, video, and summary format and presented at four different levels (based on student cognitive learning style):

(1) Individual Question Feedback. Based on the type of question asked, the tutor provides immediate feedback on whether the question was good or poor. In addition, the instructional intervention also included the question (and answer) that triggered the tutor's response.

(2) Individual Clue Classification Feedback. As students question a witness, each clue that has been revealed as a result of the dialogue must be classified as either supporting or refuting a Command, Timed, or Victim (V) device, or none of the above (Not Applicable – N/A). Based on this threat assessment, the tutor provides feedback on whether the threat assessment was correct or not, together with a rationale for the correct response specific to each clue (e.g. "There is a slowdown point that forces the target to travel through a particular area – this increases the likelihood of a command or victim-operated device").

(3) Overall Threat Assessment Feedback. Immediately after the student has completed the final assessment of the device (which effectively finishes the game), a scenario debrief is presented. The debriefing comprises a summary of the scenario's back-story, target, device type, and the critical clues that contributed to that assessment.

(4) Overall QT Feedback. After the tutor provides feedback on the student's final threat assessment, a series of training modules pertaining to each of the question types are presented. Any instance of tutor feedback during the game will trigger that specific module to be presented on the game's completion. Therefore, the presentation of modules is determined by the questioning performance of the student. Finally, each training module also includes the question (and answer) that triggered the tutor's response.

### *5.5 QuestionIT evaluation and future work*

QuestionIT builds instructional content and SA clues into questions and questioning strategy to efficiently reveal situational clues as a critical means of IED detection. Comparison between a no tutor version of QuestionIT and tutor enabled version served to evaluate the training efficacy of the adaptive feedback and instruction capabilities. One of the main performance evaluations is questioning efficiency which is determined by a ratio of the number of SA clues revealed to the number of questions asked. Other measures included realism, usefulness, and ease of use of QuestionIT. The results showed that trainees using the tutor enabled version asked fewer, yet relevant questions with improved questioning efficiency. A success rate for a following course after QuestionIT was developed and used in IEDD training school was improved to 94%. However, clue classification was no better with the tutor than without. The researchers theorized that trainees might over think the threat assessment. The overall results do suggest that the trainees' became better at QT with the tutor enabled QuestionIT and this positive gain transferred into the live role-play aspect of the training. Detailed discussions on the design, implementation, and evaluation of QuestionIT can be found in a case study of Hou, Banbury, & Burns (2015).

QuestionIT does provide interactive feedback based on the student response. This intelligent attribute depends on built-in scripts (i.e., instructional content and SA clues in the questions and questioning strategies). However, ITS developers should realize that the term "intelligence" can be defined at different operational levels. Shute and Psotka (1994) suggest that to be considered intelligent an ITS should 1) accurately diagnose the learners' knowledge, skill, or cognitive style using general principles, not scripts; 2) adapt to the learner using appropriate instructional strategies; and 3) flexibly respond to the learner over training instances. The neglected aspect of this definition is that these postulates pertain to the context of domain training and the operational environment.

The QuestionIT does necessitate a multi-modal psychophysiological metric assessment for determining at minimum attention and engagement of the trainee using Electroencephalography (EEG) and eye tracking. HRV and EDR as indirect measures of workload have been recommended for the ITS (Hou et al., 2010). In the case, of the IEDD trainer these metrics may not be sensitive or diagnostic given that there is not a stress component to training though the training task is high in cognitive load. Further investigations may include the use of EEG. EEG Data can be correlated with training content events to develop workload measures, provide the information needed to classify student cognitive learning styles, and determine the appropriate low-resolution sensors.

In summary, further QuestionIT effort to develop a generalizable ITS system will focus on a testbed approach where multiple sensors and strategies are available to determine the proper system configuration for each training domain. This approach is a systematic evaluation of integrated components over time. In other words, the process of determining metrics (sensor based or otherwise), instructional strategies, and implementation methods is an investment of time and resources with clear goals, benchmarks, and deliverables at each stage. Some training tasks may not need a cognitive state or brain based learning style assessment. Evaluating whether a task should include such measures is paramount to reducing ITS development costs and improving construct validity of the ITS design.

## 6 Conclusion

To provide guidance for the design and development of adaptive learning systems, this paper first reviewed the evolutionary progress of learning theories with the advances in computers and AI. Concepts and design models of teaching machines, CAI, ICAI, and other enabling technologies such as AugCog and associated AIA framework provide needed methodologies to develop adaptive and individualized learning systems. Second, based on common elements extracted from previous frameworks, a generic conceptual framework of intelligent adaptive learning systems was introduced to illustrated four essential system components learning situation assessment, learner state assessment, adaptation engine, and user interface. These four components are essential to work with other associated expert, learner, interaction models, etc. to make the learning system more intelligent and responsive to the learner. Third, this conceptual framework can serve as guidance for designing intelligent adaptive learning systems. Finally, a working example of an intelligent adaptive learning system QuestionIT was introduced as a customized trainer and followed a testbed approach which was then implemented into the field. It illustrates how to follow the framework and architecture discussed in the previous sections. The intent is to explain the design process for designers and developers of intelligent adaptive learning systems.

Today’s advances in technology, sensors, data analytics allow for a new generation of intelligent adaptive learning system capabilities. The testbed approach with associated conceptual framework outlined above is the first phase of truly determining the utility and effectiveness of intelligent adaptive learning systems for multiple fields of use in the ever complicated space of military training. Understanding the design and development of such systems such that they are highly effective and deployable within a few design cycles will ultimately change how learning and training are accomplished across the spectrum of society’s education and training needs.

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