Optimizing Soldier Performance Through Coaching: A Framework for Stress Intervention Research

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ABSTRACT

High-stress professions, including those in the military, medical, and emergency response fields demand the ability to perform effectively under pressure. For military personnel, managing stress effectively is crucial for mission success. While adaptive learning and Intelligent Tutoring Systems (ITSs) hold immense potential for providing personalized training, a theoretically grounded framework for developing and evaluating their effectiveness in building stress resilience is lacking. This highlights a critical research need: how can we effectively leverage adaptive training systems to improve performance under stress. This paper presents a novel coaching and feedback framework that can be used to develop evidence-based strategies that can be integrated into ITSs to enhance stress resilience and facilitate the development of essential technologies and coaching strategies.

Drawing upon existing literature on stress resilience and ITSs, the framework outlines different types of adaptive training strategies and key components needed to provide stress-aligned coaching including, 1) a learner model that retains information about individual differences in baseline physiology profiles, stress classifiers, and historical performance on stress management, 2) a domain model that embeds stress injects and context-aligned assessments for a given task or scenario, and 3) a pedagogical model that leverages the learner and domain models to select individualized coaching strategies designed to optimize performance and stress management. The framework outlines data requirements for an ITS to model and coach stress responses by establishing criteria to assess performance, populate learner models, structure instructional feedback and dynamically adjust training scenarios. A framework of this nature will be used to drive empirical studies across different coaching strategies and to train machine learning classifiers to personalize the selection of strategies based on variations across learner and domain models. Ultimately, this work will guide future research and inform the development of improved stress modeling and coaching strategies to better prepare personnel in high-stakes domains.

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INTRODUCTION

Stress is a constant and influential factor in high-stakes fields such as the military, emergency response, and elite sports, shaping performance and decision making. Stress resilience, or the ability to manage and adapt to high-pressure situations, is essential for maintaining effectiveness and well-being within these domains (Shiri Malekaba et al., 2024). Stress in these settings can be acute, as in combat or crisis situations, or chronic, and driven by long-term exposure to unpredictable conditions, demanding schedules, and life-or-death responsibilities and situations. These types of stress affect multiple facets of functioning. Stress can trigger physiological responses that elevate heart rate and cortisol levels over time, resulting in health complications later down the line; it can impair memory, attention, and judgment under pressure; and it may contribute to heightened emotional reactivity or longer-term psychological challenges. Building resilience in these contexts is not just beneficial, but mission critical.

The military presents a uniquely demanding context for stress research. Service members routinely operate in life-threatening environments that require rapid decision-making under extreme pressure. Prolonged exposure to such stress can lead to cognitive fatigue, compromised judgment, and diminished operational effectiveness. To safeguard both mission readiness and individual well-being, it is essential to implement strategies that mitigate these effects. Resilience training has become a core component of military preparation, aimed at enhancing psychological strength. Techniques such as mindfulness-based stress reduction, controlled breathing, and exposure therapy are have been used to improve emotional regulation and cognitive flexibility (Driskell et al., 2018; Hunt et al., 2018; Morrison et al., 2017; Stanley et al., 2011). Stress inoculation training, in particular, has shown promise in improving decision-making under pressure by helping individuals develop adaptive coping skills through repeated exposure to controlled stressors (Saundersl et al., 1996). Research indicates that resilient individuals demonstrate better problem-solving, quicker response times, and stronger collaboration in high-stress situations (Bekesiene et al., 2023).

Traditional military training methods, while effective, often lack personalization and adaptability to individual stress responses. To maintain readiness, modern training programs must evolve beyond traditional methods and incorporate adaptive learning technologies. Intelligent Tutoring Systems (ITSs) offer a promising solution to address these needs. By dynamically adjusting training scenarios based on real-time stress indicators, ITSs can optimize learning outcomes and improve operational readiness (Finseth et al., 2025). Research suggests that ITS-driven stress resilience training can enhance cognitive flexibility, reduce performance degradation under stress, and improve long-term retention of coping strategies (Hubal & Murphy, 2016).

In this paper, we present a coaching and feedback framework that can be used to develop evidence-based strategies that can be integrated into ITSs to enhance stress resilience and facilitate the development of essential technologies and coaching strategies. Drawing upon existing literature on stress resilience and ITSs, the framework outlines different types of adaptive training strategies that can be applied across the training timeline—before, during, and after training—and ITS dependencies needed to provide stress-aligned coaching including, 1) a learner model that retains information about individual differences in baseline physiology profiles, stress classifiers, and historical performance on stress management, 2) a domain model that embeds stress injects and context-aligned assessments for a given task or scenario, and 3) a pedagogical model that leverages the learner and domain models to select individualized coaching strategies designed to optimize performance and stress management. The framework addresses data requirements for an ITS to model to assess performance, populate learner models, structure instructional feedback and dynamically adjust training scenarios. The framework aims to assist ITS developers, researchers, and practitioners in implementing effective coaching strategies that can be applied in ITSs to support stress resilience.

BACKGROUND

Understanding how stress affects human performance and identifying training strategies that cultivate stress resilience is critical for enhancing Soldier readiness. Theoretical models of stress responses can help explain how environmental and psychological pressures influence cognitive and physiological functioning in military operations. Pomeroy (2013), in his review of the impact of stressors on military performance, discusses stress in terms of inputs, processes, and output. Inputs are the factors that induce stress. Examples include environmental conditions such as extreme temperatures or loud noise, operational demands like sleep deprivation or sustained vigilance, and psychological stressors such as ambiguous mission objectives or perceived threat to life. Processes refer to the strategies an individual may apply to cope with acute or prolonged stress. Examples include physiological regulation techniques (e.g., controlled breathing), cognitive strategies (e.g., reappraisal or attentional control), and behavioral adaptations (e.g., task prioritization or reliance on automated routines). Outputs refer to the impact of stress on performance, which can include affective, cognitive and behavioral performance related outcomes such as impaired memory, attentional tunneling, slow reaction time, decreased coordination, increased arousal, decreased motivation, and decreased situational awareness. He also notes that environmental factors such as extreme temperatures and noise can potentially reduce vigilance and psychomotor performance, especially when combined with other stressors. However, Pomeroy also emphasizes that stress is not inherently negative. Referring back to Selye's (1976) distinction between eustress and distress, Pomeroy notes that moderate stress can enhance performance, more so the case for well-trained individuals, by enhancing focus. The decline in performance occurs when stressors exceed an individual's capacity to adapt to or cope with stress. Understanding the sources, mechanisms, and impacts of stress provides emphasis for why systems, training protocols, and support strategies must accurately reflect the demands of human performance under stress.

Flood & Keegan (2022) highlight that military personnel must maintain cognitive performance despite exposure to intense psychological stressors. Their examination of psychological stress in military personnel draws upon the Transactional Theory of Stress, which posits that stress responses are influenced by an individual's appraisal of stressors as well as the coping strategies they utilize. This perspective underscores the importance of cognitive resilience, or the ability to sustain mental performance despite stress-induced disruptions. Flood & Keegan also discuss stress inoculation training, an approach that prepares individuals to manage stress by gradually exposing them to high-pressure scenarios. This is consistent with overarching military resilience programs, such as mindfulness-based attention training (MBAT) and cognitive reappraisal strategies (Riepenhausen et al., 2022). To safeguard both mission readiness and individual well-being, it is essential to implement strategies that mitigate these effects. Resilience training has become a core component of military preparation, aimed at enhancing psychological strength. Techniques such as mindfulness-based stress reduction (Bishop, 2002), controlled breathing (Zaccaro et al., 2018), and exposure therapy (Rothbaum & Schwartz, 2002) are commonly used to improve emotional regulation and cognitive flexibility. Research indicates that resilient individuals demonstrate better problem-solving, quicker response times, and stronger collaboration in high-stress situations (Entin & Serfaty, 1999).

ITSs are emerging as an invaluable tool in personalized military training, offering real-time adjustments based on learner progress and learner state levels (Kulik & Fletcher, 2016; Sottilaire et al., 2018). Individualized instruction is provided through software components that encompass three kinds of knowledge, which are typically referred to as the domain model, the learner model (or student model), and the pedagogical model (also referred to as the instructor model) (Sottilare et al., 2017).Through the incorporation of information about the knowledge of a particular domain (domain model), student skills and performance (learner model), and effective instructional strategies (pedagogical model), and by leveraging machine learning, ITSs can assess an individual's cognitive load (Sarkar et al., 2019) and provide tailored coaching strategies (Sottilare et al., 2012). These systems have the potential to enable stress inoculation, which involves individuals gradually building resilience through repeated exposure to simulated high-pressure situations (Finseth et al., 2025).

Despite advancements in training methodologies, there remains a critical gap in stress coaching research. Current programs often focus on physiological and behavioral aspects but lack a cohesive framework that integrates adaptive learning. In the following section, we introduce the framework and discuss the requirements and dependencies for developing adaptive training based on personalized stress inoculation. Then, we discuss evidence-based strategies that can be integrated into ITSs to enhance stress resilience and facilitate the development of essential technologies and coaching strategies. As with traditional ITSs architectures, adaptive stress resilience training driven by ITSs requires the integration of a domain model, learner model, and pedagogical model. Each model contributes information needed to effectively enhance training and adapt instruction to individual learners. In discussing the proposed framework for stress training, we outline the data inputs needed to populate these models within the context of stress resilience research and training.

PROPOSED FRAMEWORK

Figure 1 illustrates how the proposed coaching and feedback framework operates across the training timeline –before, during, and after training–by integrating key ITS components (Learner Model, Domain Model, and Pedagogical Model) with data sources (Sensors), intelligent system functions (ITS), and delivery mechanisms (Interfaces). The framework shows how coaching interventions can be informed by real-time and historical data, enabling adaptive instruction at both macro and micro levels. Before training, sensor data and learner model parameters (e.g., baseline physiological profiles, prior stress performance, self response questions) can be used to personalize scenario selection and preparatory coaching. During training, real-time sensor inputs and task assessments allow the ITS to monitor stress responses and adapt scenario elements or deliver in-the-moment coaching. After training, the system supports reflection and reinforcement through personalized AARs, guided by insights from the learner and pedagogical models. The framework emphasizes the interaction between models and data streams across the full training cycle, highlighting the importance of modular, evidence-based components that support adaptive, stress-aligned instruction.

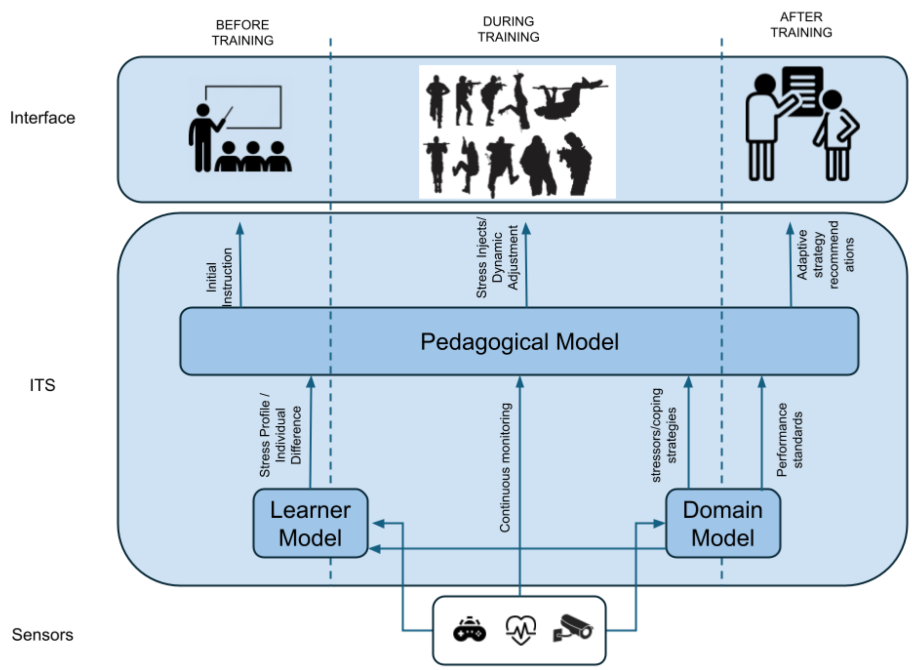

Figure 1. A Framework for Coaching Stress Resilience

Learner Model

In an adaptive training system for coaching stress resilience, the Learner Model identifies and logs individual differences in stress reactivity and performance. By integrating physiological baselines, real-time stress classification, and historical performance data, this model enables adaptive systems to tailor interventions that promote resilience and optimize learning under pressure. To account for individual differences between learners and effectively model stress responses, the Learner Model establishes a baseline physiological profile for each individual based on information collected under non-stressful conditions. By comparing real-time data against these baselines, the system can identify deviations that indicate acute or chronic stress responses in an individual.

The Learner Model also incorporates stress classifiers by using real-time physiological data and historical performance trends to detect and categorize stress responses. These classifiers can be developed using machine learning algorithms that analyze patterns in heart rate variability (HRV), galvanic skin response (GSR), respiration rate, and pupil dilation as well as behavioral data to identify high stress moments during training events. The use of these classifiers allows the system to differentiate between stress states and allows the system to generate a more accurate profile of the learner's cognitive and emotional state. The use of adaptive classifiers will allow for a constantly evolving profile that continuously takes in new data in order to provide highly personalized predictions that are tailored to both the individual learner and the context of the experienced stressors. Research has shown that such adaptive models can reliably predict stress levels and even identify early indicators of cognitive overload or emotional distress (Pellegrin et al., 2025). When integrated into an ITS, these classifiers enable the system to accurately assess stress responses and dynamically adjust instructional pacing, task complexity, and feedback strategies to support optimal learning under pressure. For example, if the system detects signs of acute stress, such as low heart rate variability, during a high-fidelity simulation, it might reduce task demands, prompt a self-regulation or coping strategy, or initiate a brief recovery period. Conversely, moderate stress can support learning by increasing engagement through challenging tasks. The use of ITSs can facilitate stress inoculation or stress resilience training by allowing learners to adapt in real time and build resilience while continuing to perform under pressure rather than becoming overloaded during a non-adaptive form of training.

Longitudinal tracking of stress management performance is another critical component of evaluating learner progress and refining coaching strategies over time. Within the Learner Model, ITSs maintain records of the learner's previous stress responses, including physiological responses, behavioral patterns, and task performance under varying levels of pressure. This data allows the system to identify trends, such as improvements in cognitive performance, recurring stress triggers, or any changes in the learner's ability to effectively employ coping strategies, to then generate personalized feedback that evolves as the learner progresses. Machine learning algorithms can also analyze these data streams to detect changes in stress resilience and therefore allow the system to anticipate potential breakdowns in performance (Oroke, 2024). For example, a learner who consistently has elevated heart rate and slower reaction times during complex decision-making tasks may benefit from interventions that target this performance decrement such as scenario-based rehearsal or guided breathing protocols. As the system gathers more data, it can adjust how often, how intensely, and what type of coaching it provides in order to tailor support to each learner's progress. This ongoing monitoring helps keep learners engaged and builds resilience by making feedback timely, personal, and rooted in their past experiences. By using learners' historical information, ITSs can deliver coaching that not only strengthens current coping strategies but also helps learners adapt and apply those skills in new and more demanding/stressful situations.

Domain Model

The Domain Model facilitates personalized training by defining the context in which the learner is likely to encounter stress, enabling the simulation of real-world, high-pressure scenarios that mimic operational demands. This model is essential for embedding stress injects, or stress-inducing elements, and performance assessments that align with the learner's specific domain, whether it be military, medical, emergency response, or other high-stress environments. Stress injects are the introduction of deliberate scenario modifications that are designed to simulate high-stakes conditions and induce stress. These injects can come in the form of unexpected events, time constraints, resource limitations, and ambiguous instructions, all of which are known to increase cognitive load (Joseph et al., 2020). Embedding stress injects into training scenarios facilitates controlled exposure and measurement of stress responses which can be used to inform stress coaching strategies. Injects within a simulated combat scenario may take the form of equipment malfunctions, sudden changes in mission objectives, or conflicting orders from leadership. For instance, Carroll et al. (2014) found that including difficult decision-making tasks as well as socio-evaluative stressors in a simulation-based training exercise increased stress responses and perceived stress. Importantly, the effectiveness of stress injects depends on how well they align with the actual demands of the task context. When the injects accurately represent the cognitive and operational stressors that learners are likely to face during a real-life scenario, they create more impactful training experiences. In addition, the Domain Model also defines context-relevant performance metrics that accurately reflect task demands and incorporate expert-driven benchmarks, enabling the ITS to evaluate learner performance and adapt training accordingly.

Pedagogical Model

The Pedagogical Model facilitates adaptive training by forming coaching and remediation strategies and using information about the trainee from the Learner Model (e.g., physiological stress markers, historical performance) and information about the task from the Domain Model (e.g., scenario complexity, stress injects) to select interventions, and dynamically adjusts task difficulty to tailor instruction (Sottilare, Graesser, Hu & Goldberg, 2014). For example, in a hypothetical, adaptive mission rehearsal scenario developed for squad leaders, the Pedagogical Model can dynamically adjust the complexity and operational tempo based on real-time assessments of cognitive load and stress indicators. If a leader demonstrates effective decision-making under moderate stress, the system may increase the scenario difficulty by introducing elements such as time constraints, ambiguous intelligence, or unexpected environmental stressors. Alternatively, if the squad leader exhibits symptoms of cognitive overload such as delayed responses or reaction times or increased physiological signs of acute stress, the system can offer guided review, lower task difficulty to allow for recovery, or stop the scenario altogether. This approach draws from the principles of stress inoculation by gradually increasing exposure to stressors while maintaining performance within the learner's adaptive threshold (Meichenbaum, 1985). The system will refine its instructional strategy over time based on the squad leader's prior performance and tailor instructional interventions to enhance stress resilience for future missions.

Implementation Across Phases of Training

As depicted in Figure 1, the collaboration between learner, domain, and pedagogical models enables ITSs to assess stress responses, adapt training conditions, and deliver precision coaching throughout the learning process. Implementing this stress coaching framework within ITS architectures requires a modular, data-driven approach that accommodates real-time adaptation, domain transferability, and empirical validation. Adaptive support spans all training phases—from pre-training assessments and tailored scenario selection to real-time stress modulation during training, and post-training feedback through individualized AARs. This section outlines the key dependencies and component-level requirements for operationalizing the framework in practice, with attention to system interoperability and learner-centered design.

Pre-Training

The pre-training phase of stress resilience instruction in an ITS establishes the baseline for personalized learning, enhanced learner readiness, and effective adaptation across iterative training sessions. Implementation within the pre-training phase requires specific technical infrastructure to ensure accurate learner modeling, meaningful priming, and responsible data use. As previously discussed, validated assessment instruments are necessary for collecting baseline stress responses. Instruments like the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) and the State-Trait Anxiety Inventory (STAI)(Spielberger et al., 1971) can be used to assess cognitive stress levels, whereas physiological sensors can measure HRV and electrodermal activity. These instruments are a necessary part of building the initial learner model and baseline profile needed to tailor training scenarios and select difficulty levels and coaching methods based on the individual learner.

In order to maximize the adaptive potential of the ITS, the system must also be capable of incorporating pre-existing learner data from various external sources whether it be a Learning Management System (LMS), wearable biosensors, or psychological profile databases. To ingest and use data from other sources, middleware or API-based data pipelines are necessary. For example, data regarding prior exposure to operational stress, trait-level resilience scores, or performance trends from previous simulation-based training can be collected and stored in the local learner model profile informing scenario pacing and the selection of initial coaching strategies. Integrating this type of data allows the ITS to enhance the personalization of early interventions by enabling the system to incorporate data obtained outside of the ITS. Trait-level variables, such as baseline anxiety, cognitive flexibility, or prior coping efficacy, can be drawn from validated instruments or historical training records and can be used to form a learner profile before instruction begins and support macro-adaptations. As a result, the ITS can begin training from a more informed starting point, eliminating the need to rebuild the learner model from the ground up and avoiding unnecessary repetition of training to collect data already available within another system.

In addition to collecting baseline measures of stress responses to inform adaptive decisions, training content can also be provided in the pre-training phase to educate trainees on the impacts of stress on performance. Initial instructional modules on stress physiology, cognitive coping strategies (like reappraisal and attentional control), and performing under pressure can deliver essential information and also get learners mentally ready to engage. For example, a short lesson on the body's stress response could include diagrams showing how the nervous system reacts, combined with a brief real-world story to build understanding. Interactive exercises could walk learners through reframing techniques in context-specific situations. These early modules also act as mental reference points: during high-stress moments, the ITS can refer back to them to reinforce key ideas and support performance. This helps learners stay oriented and builds trust in the system as they move into more complex challenges. Together, these pre-training components establish the foundation for dynamic adaptation during live training, where the system continuously interprets learner inputs, adjusts instructional strategies, and delivers coaching in real time based on the evolving learner state.

During-Training

Adapting training content during training is a key feature of ITS. During training, an ITS can employ a range of coaching strategies or interventions based on learners' past performance and how they have managed stress under different training conditions. While initial instructional modules may have informed the learner about the coping strategies to use to mitigate stress prior to training like cognitive reappraisal, self-regulation, and metacognition, during training an ITS can provide hints, prompts, feedback, and scenario adjustments to support in situ stress resilience. Table1 provides examples of stress coaching strategies that can be implemented during training. These strategies can be dynamically adjusted and employed based on the learner's stress profile.

Adaptive coaching, however, cannot occur in isolation. To detect stress during training, the ITS should leverage multimodal data streams that are capable of detecting both physiological and behavioral indicators of stress to assess stress states and prescribe coaching interventions. Examples of multimodal data that can be used to infer stress in real-time include heart rate (HR) and metrics for variability (HRV), galvanic skin response (GSR), electroencephalography (EEG), pupillometry, and behavioral performance metrics (e.g., task completion times, error frequency, hesitation duration). Previous research has shown strong linkages between these data and indicators of stress, including autonomic arousal, cognitive workload, and attentional focus (Beatty, 1982; Fairclough, 2009; Thayer et al., 2012).

Affective computing, which introduces the capability for an ITS to recognize the learner's emotional state, whether it be boredom, confusion, or frustration, and incorporate this into the coaching strategies it employs, is an emerging research area that can inform best practices for during-training coaching and adaptation (Calvo & D'Mello, 2010). Affective computing relies on sensing technologies and machine learning techniques to interpret and classify multimodal inputs such as facial features, speech, body language, and physiological responses into classification states to dynamically adjust the ITSs pedagogical strategies (D'Mello & Graesser, 2013; Dorneles et al., 2023). A key attribute of affective computing is its emphasis on context-aware analysis, which means that learners' affective states are interpreted within the context of task demands, learner profiles, and environmental conditions (Dorneles et al., 2023). For example, elevated heart rate variability may be an indicator of adaptive engagement in one context but an indicator of cognitive strain in another. By incorporating context within its classification of the learners affective or cognitive state, the ITS can deliver more precise and personalized coaching adaptations and feedback. These insights are fed into the pedagogical module and allow the system to adjust instructional content as well as emotional tone, pacing, and support strategies.

The integration of physiological data streams in real time into an ITS, through wearable devices or embedded peripherals, requires a balance between fidelity, unobtrusiveness, and ecological validity. The ITS must be able to combine these data streams into a learner model that tracks and classifies learner states to inform instructional strategies and coaching actions. In addition to assessing stress states, an ITS must also introduce context-aligned stress injects within training scenarios to induce (or reduce) stress. These injects may include time constraints, ambiguous orders, simulated failures, or evaluative pressure, and should be aligned with real-world stressors that are encountered in the domain of interest (Driskell & Johnston, 1998). To refine a learner's exposure to stress, the ITS should include a scenario tagging and scheduling engine that aligns stress injects with specific cognitive, emotional, or task-level demands, which allows the system to introduce stressors at instructionally relevant moments (Feigh et al., 2012). For example, the ITS might impose elements of time pressure if the learner shows signs of overconfidence, or it might introduce ambiguity to the scenario if it detects cognitive load is low and that engagement is decreasing. Trigger logic, which may be time-based, performance-based, or affect-driven, depending on the instructional context, can be used to ensure that stressors are introduced at instructionally relevant moments based on the flow of the scenario and the real-time learner state (Finseth, 2025). The use of this logic builds on principles of stress exposure training which emphasize matching the stressor type and intensity to task demands (Driskell & Johnston, 1998). To ensure that stress injects support engagement without inducing cognitive overload, the ITS must calibrate stressor intensity relative to the learner's adaptive threshold.

Using this learner state information, an ITSs can identify, deliver, and dynamically adjust instructional interventions, through its pedagogical module. Examples of coaching interventions that an ITS can apply to promote stress management include cognitive reappraisal prompts, pacing adjustments, or suggested emotion regulation (Table 1). For example, cognitive reappraisal is a skill that involves critically examining one's initial interpretation of a situation in order to deliberately influence their emotional response (Southward et al., 2021). The technique has been demonstrated to successfully help individuals reduce their negative emotions surrounding a stressful event (Ochsner et al., 2002; Southward et al., 2021). Jamieson et al. (2010) demonstrated that participants instructed to reappraise their arousal as a challenge that enhances performance while taking the GRE test exhibited reduced sympathetic nervous system activation and better performance on the test than participants in the control group. Cognitive reappraisal prompts delivered through an ITS can include audio or visual prompts that guide learners to reframe their mindset around a stress-inducing stimulus or event. The goal is to encourage the learner to shift their appraisal of the stressor from "threat" to "challenge." Another potential intervention, physiological response regulation, or biofeedback, involves using sensed stress responses like increased heart or breathing rate to prompt learners to consciously adjust their response. Within an ITS, this could be executed through visual or auditory cues that inform the learner that they've entered a stress state. For instance, Harris et al., (2014) utilized auditory biofeedback to successfully encourage users to slow their respiratory rate. Adaptive scenario pacing presents another potential coaching intervention wherein the system adjusts scenario difficulty or intensity in real-time. Maraffino et al., demonstrated that training sessions in which adaptations occurred during training produced increased performance gains over training sessions for which adaptations occurred before or after the session.

Table 1. Coaching Strategy Implementation

Coaching Strategy	Implementation Mechanism	Dynamic Adjustment Logic
Cognitive Reappraisal Prompts	Visual/audio dialogue modules linked to stress interpretations	Triggered by cognitive indicators of threat-based appraisal (e.g., error spike, hesitation latency)
Physiological Response Regulation (Biofeedback)	Interventions tied to biometric thresholds	Activated by real-time HRV dips or EDA spikes; intensity modulated based on recovery rate
Emotion Labeling & Micro-Reflections	Brief check-ins via chatbot or sidebar agent	Initiated periodically or after high-arousal segments; frequency adapted to learner tolerance
Visual Feedback (e.g., "stress gauge")	Visual overlays or ambient UI cues (color gradients, icons)	Dynamically rendered based on stress index composite score
Scenario Simplification or Pacing Control	Task branching engine with graded difficulty	Triggered when coaching fails to restore baseline after N interventions

Effective coaching strategies involve aligning interventions with the learner's current stress response and historical stress response. Within an ITS, this means coaching strategies are not triggered solely by threshold-based indicators (e.g., elevated GSR), but by patterns interpreted in relation to learner history, task complexity, and instructional goals (Sottilare et al., 2014). For example, if a squad leader has previously demonstrated improved performance following physiological regulation techniques during high-tempo mission simulations, the pedagogical model can prioritize similar interventions when similar stress patterns are detected. The ITS can provide support in real time, based on performance trends and inputs from the learner model, rather than waiting for performance to decline. In this case, this may manifest in the form of a prompt from the ITS to utilize a breathing technique to mitigate negative impacts from stress in real time. Similarly, if cognitive reframing prompts have previously helped support planning performance and decision making under moderate stress, the ITS can schedule those interventions earlier in similar scenarios to reinforce adaptive appraisal strategies in subsequent training sessions.

Post-Training

In contrast to during-training interventions that focus on stress regulation in real time and adaptive support, the post-training phase focuses on reflection, ensuring that learned skills are retained and transferable across contexts. The dependencies for implementation within an ITS in this phase include capabilities for adaptive debriefing, collection and storage of longitudinal data, and learner-facilitated review tools.

The goal of implementing these capabilities is to prompt learner reflection through self assessment. These capabilities should allow learners to revisit or replay key critical events from training, review their stress responses, and identify successful stress regulation strategies. Grounded in cognitive reappraisal theory (Gross, 1998), this process supports the reframing of stress not as a threat, but as a challenge to be managed. Within military applications of structured review, this can take the form of after-action reviews (AARs) which allow soldiers to reflect on what happened, why it happened, and how to improve (Meliza, 1996). To implement this type of capability within an ITS, several technical dependencies must be addressed. In order to identify critical points of performance or stress injects, the system must be capable of tagging these events for later review. Furthermore, synchronized playback capability and data overlays enable learners to go back and review stress events accompanied by real-time sensor and performance data.

Supporting longitudinal tracking of learner performance and stress adaptation over time requires the integration of a scalable infrastructure capable of storing and retrieving multimodal data over time and across sessions. This allows the system to track and access learner stress trajectories, intervention history, and performance metrics that can be used to further refine the learner profile, inform adaptation of subsequent training sessions, and populate structured after-action reviews and learner guided review of performance under stress.

Interoperability with external learning systems enhances an ITSs capability to provide adaptive coaching by extending instruction beyond the capability of the ITS alone. From a technical perspective, compatibility with established interoperability standards like xAPI, which allows the ITS to plug into external LMSs and simulation environments, facilitates the ITSs capability to sync learner data like progress metrics and coping strategy responsiveness with other learning platforms (Streicher etal., 2019). By integrating with a broader training ecosystem, skill retention and transfer of adaptive strategies are enhanced by opening up possibilities for alternate training modalities which enables continued reinforcement across platforms and a greater capacity for variation in stressors, scenarios, and skill application. For example, the Generalized Intelligent Framework for tutoring (GIFT) is a modular, open-source architecture designed to support interoperability across ITS components. It supports integration with external simulation environments, learning management systems, and physiological sensors which makes it ideal for extending post-training capabilities across platforms (Sottilare et al., 2018). Given that simulation-based training presents a viable option for high-fidelity stress resilience training, this capability is particularly critical for coaching stress resilience (Alice et al., 2025).

DISCUSSION AND FUTURE RESEARCH

Drawing upon existing literature on stress resilience and ITSs, the framework outlined in this paper presents key components needed to provide stress-aligned coaching across pre-, during-, and post-training phases. Central to providing these services are 1) a learner model that retains information about individual differences in baseline physiology profiles, stress classifiers, and historical performance on stress management, 2) a domain model that embeds stress injects and context-aligned assessments for a given task or scenario, and 3) a pedagogical model that leverages the learner and domain models to select individualized coaching strategies designed to optimize performance and stress management. The framework outlines data requirements for an ITS to model and coach stress responses by establishing criteria to assess performance, populate learner models, structure instructional feedback and dynamically adjust training scenarios.

A notable contribution of the framework is detailing requirements to support coaching before, during and at the conclusion of training. The pre-training phase establishes crucial baselines and primes learners with foundational knowledge to prepare them for upcoming training interactions. The baselines established in this phase can be used to set initial training conditions. The during-training phase establishes dependencies for supporting real-time assessment and coaching. The integration of multimodal data streams, including heart rate variability, galvanic skin response, and pupillometry, enables ITSs to accurately classify stress states and trigger timely coaching strategies. Facilitating context-aware analysis within affective computing further refines the precision of these interventions, ensuring that coaching is not only responsive but also relevant to the learner's specific situational demands. Furthermore, the post-training phase, with its focus on structured reflection and longitudinal data tracking, highlights requirements for long-term skill retention and transfer, noting the importance of leveraging standards like xAPI to form robust learner models that can keep longitudinal records of performance data and stress coaching intervention effects to drive more effective coaching strategies and scenario adaptations.

The coaching strategies presented in our framework are a foundation for the types of feedback strategies and tactics that can be applied in ITSs to support stress resilience training. The framework can be used to configure and investigate feedback and coaching strategies to determine the best mix of coaching to deliver before, during and after training. Future research should investigate the creation of data-driven stress coaching models based on the strategies outlined in the framework using ITS platforms such as GIFT. GIFT provides a range of features and functionality that align with the requirements of adaptive coaching and feedback in synthetic training environments, including sensor modules for assessing physiological states, domain modules for assessing key performance indicators, mechanisms for developing and delivering pre and in-situ feedback and coaching, and opportunities for reflective assessment and feedback through the GIFT GameMaster interface. Future research should also investigate approaches and models for training machine learning classifiers to personalize the selection of strategies based on variations in stress states across both learner and domain models. Developing classifications that demonstrate transfer learning will be critical for developing modular and robust state classification algorithms that can be used across activities and training scenarios.

CONCLUSION

Stress resilience is a critical component of readiness in high-stakes environments. This paper outlines a framework for integrating adaptive stress coaching into Intelligent Tutoring Systems using three core models: learner, domain, and pedagogical. By capturing baseline physiology, modeling task demands, and delivering real-time coaching aligned with individual needs, this approach supports tailored instruction across the training timeline. The framework offers a starting point for designing ITSs that adapt to learners' evolving stress profiles. It also highlights the system requirements—both technical and instructional—for delivering personalized, evidence-informed support before, during, and after training. Future work should focus on validating these strategies in applied settings and developing machine learning approaches that refine coaching based on performance patterns and contextual variables. Ultimately, systems built on this framework can help learners build resilience, adapt under pressure, and retain skills that matter when stakes are high.

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