How, When, and What to Adapt: Effective Adaptive Training through Game-Based Development Technology

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ABSTRACT

Adaptative training provides opportunities to administer learning or training content to the right people at the right time. This form of training has many benefits including increased skill mastery, optimal challenge level, and enhanced engagement. An instructional designer can adapt training through changing the content itself, such as creating a more difficult environment, providing autonomy to the trainee, or modifying the interface display features or feedback to assist trainees (Zahabi et al., 2020). Adaptive training can also take place within a training instance or across trainings. This presents many opportunities to intervene and improve training but should only be implemented on elements that serve the training goals and at the right time. Considering adaptive strategies can, in some instances, increase training time (Sampayo-Vargas et al., 2013) and at times may incur higher development costs, it is important to ensure that instructional designers aim to implement adaptive capabilities where value can be gained. In addition, newer technological advances in simulation technology, physiological sensors, and integration technology allow for the assessment of trainee states live and unobtrusively. We posit that these technologies can mitigate the potential negative impacts of adaptive training and instead provide the users with real-time adaptations and in meaningful ways to serve their training goals. This paper will discuss different methods and approaches for adapting training content and provide guidance for the right implementation of various adaptive strategies. A low-cost experimental adaptive research testbed idea will be presented, allowing for the exploration of different strategies for measuring and adapting content utilizing game-based development technology. Discussions of the benefits and shortfalls of different adaptive decision logics, criteria, and adapted content will provide training designers with guidance on which adaptive strategies to use, under what conditions, and how to implement these strategies in modern training environments.

ABOUT THE AUTHORS

Dr. Summer Rebensky, Scientist, Aptima, Inc., has a background focusing on human performance, cognition, and training in emerging systems. Dr. Rebensky has previous experience as a research fellow as a part of the Air Force Research Laboratory conducting research on drone operations and human-agent teaming utilizing game-based technology. Her research experience involves leveraging Virtual Reality (VR), Augmented Reality (AR), and game-based technology to optimize human performance in training and operations. Dr. Rebensky received her BA in psychology, MS in aviation human factors, and PhD in aviation sciences focused on human factors from Florida Tech.

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INTRODUCTION

Training in the modern era necessitates leveraging the technology we have to its fullest potential. In 2020, General Brown, the Chief of Staff for the U.S. Air Force, challenged the air force to accelerate change or lose. "The processes with which we build capabilities for our Airmen have not adapted to these changes; the ways in which we test, evaluate, and train with them do not meet current or future demands" (Brown, 2020). Adapting to the times must also mean the training can adapt to the needs of the trainee. Individualized and adaptive training, which revolve around the needs of each specific trainee, have been shown to be effective compared to traditional instructor and non-adaptive computer-based training in a variety of topics and domains (Ma et al., 2014). Examples of adaptive training gains include improved accuracy in an electronic warfare trainer (Van Buskirk, 2019) and improved performance as well as shorter timelines to reach desired proficiency (Billings, 2012). As a result, military training programs can benefit from adaptive instructional techniques (Spain et al., 2012). With efforts such as multi-capable airmen, our warfighters must adjust and adapt to their environment, so too must the training. Guidance for specifically what and how to adapt are questions that are critical to adaptive training and have only begun to be addressed in recent years (Spain et al., 2012). With high costs for building an adaptive system, designers should ensure the *when, how,* and *what* to adapt are implemented accordingly in ways that serve the training goals. Ensuring the military has methods to rapidly determine adaptive strategies will ensure effectiveness from adaptive training systems (Bauer et al., 2012). With advancements in technology and simulation development technologies, building an adaptive system can be more attainable than ever. Adaptive systems can be developed rapidly and made extensible in ways that serve research, operations, and training design that can evolve with the warfighter needs.

This paper aims to describe a process for developing game-based adaptive training which can be developed and employed to enhance proficiency-based training. This will be accomplished through first providing a foundational understanding of different types of adaptation strategies, when to employ them, and how to design and execute them. Then the foundation will be built upon to determine what are the inputs that adaptive systems need in order to appropriately select an appropriately individualized training path for a learner. Finally, a process in which to build modern adaptive systems which can serve training and research in adaptive systems will be presented utilizing game-based development technology.

ADAPTATION STRATEGIES

With the need to have more specialized individuals across a variety of fields and the requirement for a faster time to readiness, there is a need to personalize training and adapt strategies more efficiently. This requires a deep and well known way of adapting training to better suit the needs of the individuals engaging with information. Adaptive strategies use a multifaceted approach to determine the optimal balance to build an adaptive system and to ensure the training goals are being achieved appropriately. Questions regarding the "when", "how" and "what" of adaptation must be asked and answered and their interrelated elements must also be considered. The following sections will describe common approaches and strategies for adaptive systems. The sections will discuss how they are commonly approached in traditional training settings and how simulation can be leveraged to address each strategy more effectively as well as constraints for implementing adaptive strategies to their fullest capabilities.

When to Adapt

Within traditional classroom settings, adapting content can be accomplished at a macro or micro level. With respect to macro adaptation, instructors or trainers may assess the performance of a class or unit after completion of a course or unit within the course. Instructors can assess if performance was low on a particular subject and, as a result, spend more instructional time on that subject for the next incoming class. Instructors may also assess how students are grasping the material using quizzes or unit tests and as a result adapt the upcoming lessons to focus more thoroughly on topics with poor performance. To tailor content at the beginning of a course, an instructor may assess the expertise level of an incoming class as a whole and as a result tailor the content to the class demographic background. For example, an incoming class of aircraft maintainers may not be new to aircraft maintenance, but new to the aircraft of interest and, as a result, maintenance procedures unique to that aircraft may be the bulk of the training. The benefit of tailoring the content to the individual is an approach that allows the instructor the freedom to emphasize content within the class based on the needs of the group and also use aptitude treatment interaction (ATI) in which some training approaches are ideal for specific individuals (Landsberg et al. 2012). Macro adaptation is a generally low-cost approach and can provide greater value and improved training effectiveness in the time allotted. For this approach, the decision of what and how to adapt are determined beforehand (Spain et al., 2012). However, macro adaptation approaches may not best serve the interests of each individual and generally do not expedite the training time required.

Micro-level adaptation aims to tailor the learning content to an individual's specific training needs. This type of adaptation poses the highest potential gains when built into training. In a traditional classroom setting, it becomes much more difficult to adapt training to serve the individual. The usual way is to provide placement exams which would then place individuals into remedial or advance class structures. However, in simulated or virtual training, the possibilities of tailoring content to the individual becomes much easier. Simulators are more accessible to trainees than live training; with the ability for data and intervention, simulation affords adaptive training (Carroll et al., in press). Adapting can occur between learning instances or even during a learning instance. As a result, there is greater potential to optimize and expedite training to each individual trainee's needs. However, the architecture and systems to build adaptive training require a hefty amount of investment and development time. Macro-adaptation can be quick and low-cost but does not best serve the individual trainee. Micro-adaptation can allow for higher gains but is generally high cost while requiring models, assessments, as well as foundational knowledge from the development, data science, and learning science domains, making it a resource intensive option (Spain et al., 2012). Adaptive training can be worth the costs if it leads to the desired outcomes. With advancements in simulator technology, game-development software, and machine learning, it is easier than ever to develop a robust and effective adaptive training simulation. The following sections will describe the aspects to consider when developing an adaptive system and how game-based technology can be leveraged for low-cost and rapid adaptive training (see "when" section of Figure 1).

How to Adapt

In simulated environments, the difficulty of training scenarios can be altered with specific techniques. For example, in Bauer et al. (2012), different adaptive strategies included increasing difficulty and dynamic adaptive. In the increasing difficulty strategy, the trainee receives a more difficult mission as time progresses and each training scenario is completed. The next scenario always increases in difficulty and does not decrease. In some designs, this may require repeating of a specific training scenario until an ideal performance score has been reached and then the trainee may advance to the next level of difficulty. In the dynamic adaptive strategy, the next scenario is based upon the performance on the previously completed training scenario. The aim is to keep trainees within an optimal level of difficulty by providing more or less difficult future scenarios based on previous performance (Ariali & Zinn, 2021). The optimization of this approach can benefit mastery level training as well as keeping trainees within a flow state (Issenberg et al., 2005; Plass, Homer, & Kinzer, 2015). Dynamic adaptive training has also been shown to be beneficial for those with specific personality traits such as high openness and neuroticism (Bauer et al., 2012).

Although these are the most common forms considered when developing adaptive training, other forms of adaptation include altering the sequencing of content to prioritize early and often exposure to content with which students are demonstrating less familiarity (Kellman, et al., 2013). Other adaptation may also include self-paced training, in which the trainees guide their training pace with computer-led instruction. which can reduce costs and time to complete training (Carey et al., 2010). Adaptation may also just include tailored feedback or goals after each training scenario.

Providing trainees feedback specific to their performance can lead to performance gains faster (Billings, 2012; see "how" section of Figure 1).

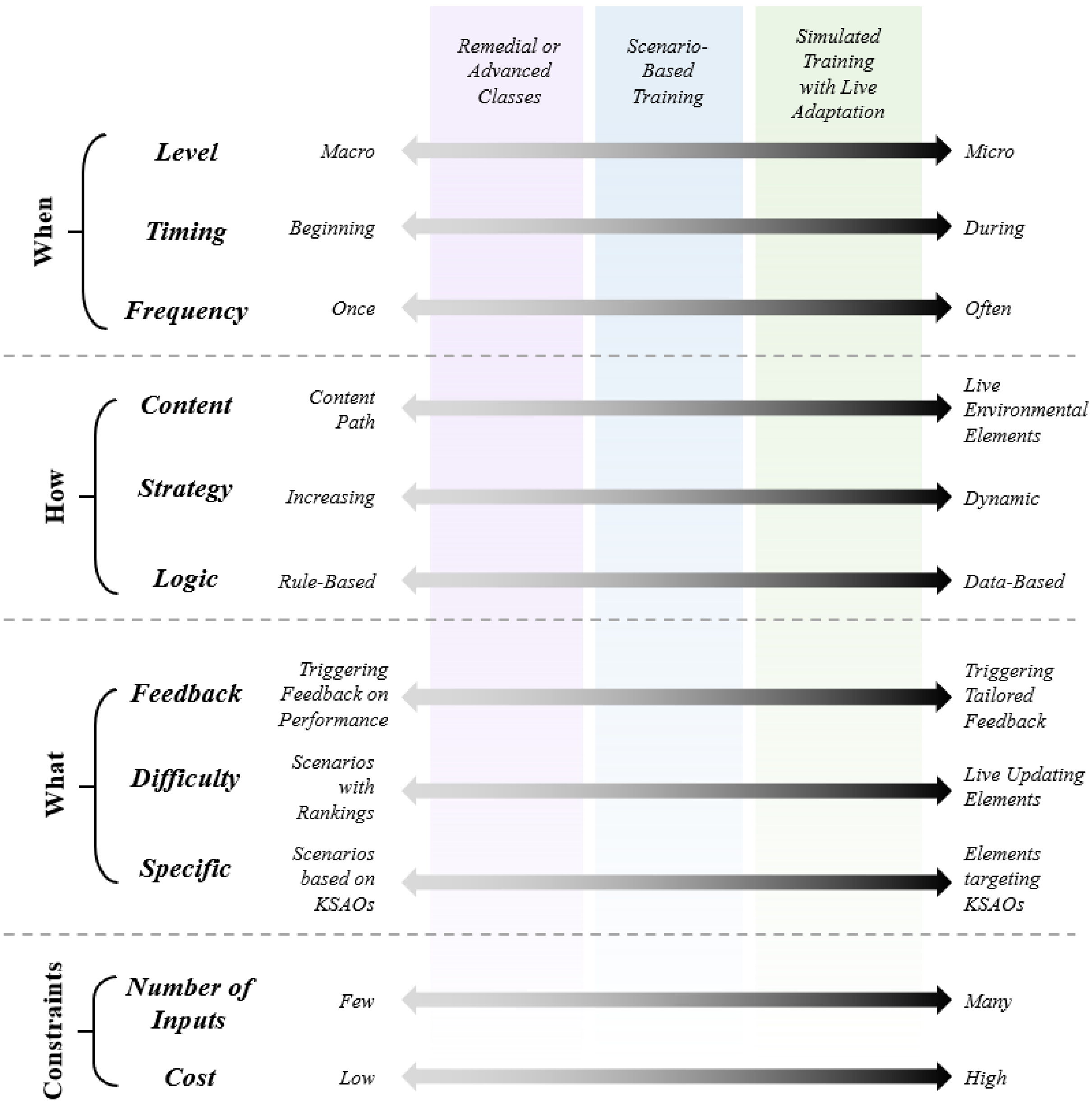

Figure 1. How, When and What to Adapt

What to Adapt

Once we have determined when and how to adapt, the adaptive system must be designed to augment the training content. In traditional training environments, adapting the content may simply mean making content more surface level, more in-depth, remedial courses, or advanced courses. In simulation environments, there is more opportunity on what is adapted down to the smallest details. In earlier computer-based adaptive training, the most common approaches were to either increase or decrease training difficulty by providing different scenarios or to adapt feedback given after performance on a particular scenario (Billings et al., 2012; Bauer et al., 2012). For example, using a game-based development software, an adaptive mental rotation task provided more or less difficult trials dependent on the trainee's performance on the previous trial (Ariali & Zinn, 2021). For feedback, trainees may receive detailed feedback related to specific learning objectives based on their level of performance related to each one (Billings et al., 2012).

Within modern-simulation development, environments can be procedurally generated, scenarios can be randomized, and Artificial Intelligence (AI) can be more robust. Databases of learning scenarios could be generated automatically and ranked based upon level of difficulty, which can be an effective approach for targeting skill proficiency. Scenarios can also be ranked, based upon the Knowledge, Skills, Abilities, and Other characteristics (KSAOs) we aim to improve. For example, a medical scenario may focus more on the ability to detect anomalies in vital signs as opposed to hands-on procedures. By grading the scenarios based upon the KSAOs they highlight, the proper trainee scenarios can be loaded One way to adapt live training is to make enemy Artificial Intelligence (AI) more difficult as trainees improve in performance (Bauer et al., 2012). In the use case of AI-based enemy infantry units, these AI may become more accurate when shooting or increase in numbers. AI may also become more strategic to hide behind cover more often, or advance using more effective pathways. Some AI may also have behaviors that respond based upon trainee interactions. AI may only become aggressive once the trainee initiates an attack, AI may start to mimic user behaviors or utilize other assets such as grenades if the trainee is exclusively hiding behind structures. AI adaptation can help prevent habituation and dynamically increase difficulty to ensure a more comprehensive skill training. This approach could also be useful for stress-habituation or engagement to keep users at a right level of arousal. By providing new or dynamic stimuli, such as dynamic AI behaviors, the training can keep the trainee on edge for the full duration of the training—simulating real world combat scenarios. If attention or search patterns are the skill being trained, then adaptive content may be cued when systems are unattended to for extended periods of time. If trainee states or performance begins to drop, the scenario can notify or alert the trainee to attend to systems, thus engraining procedural behaviors (see "what section of Figure 1). Each of these approaches offers clear value for improving training, What to adapt, along with previous discussions of how and when to adapt, will depend upon the constraints of costs and the number and types of inputs feasible within the system (see "constraints" section of Figure 1).

DESIGNING ADAPTIVE SYSTEMS

Effective adaptive systems receive the trainee's states that relate to the desired outcomes and adapt based upon them (Sottilare, 2015). Knowledge elicitation of the training goals and desired outcomes is vital to ensuring the right adaptation strategy. Developing adaptive training by starting with cognitive task analyses and modeling can allow the design of the simulator to accurately capture ideal learning and behavior for novices through experts. For example, a virtual medical trainer utilized cognitive task analyses and an ACT-R model to classify when learning was occurring, as well as levels of skill decay, to provide optimal training for desired levels of competence (Siu et al., 2016). In teams research, extracting predictors of team performance, such as cohesion, conflict, and leadership, can be used as the guidance for behavioral markers to formulate team states—allowing for the states to guide the when, how, and why for adaptive team training (Sottilare, 2017). By ensuring that we are capturing all of the knowledge, skills, and abilities of relevance, and as a result, adapting the environment specifically to target those deficits, we can ensure the adaptation serves improving the trainee needs. We must start by asking: What are the end goals? Are our inputs serving the algorithm that targets what we want to improve?

Adaptation Inputs

In educational settings, adapting the content can be accomplished through providing feedback, changing the sequencing of the content, scaffolding the content, or altering the view of the material (Shute & Zapata-Rivera, 2012). With the addition of simulation, we can adapt training scenarios themselves or dynamically change environments—the world is our oyster with a whole new issue. What do we adapt when everything is an option? One key issue with existing adaptive technologies is the lack of controlled experiments to estimate the true cost-to benefit ratio of adaptive systems (Shute & Zapata-Rivera, 2012). Therefore, with a large cost undertaking of building an adaptive training system, we want to ensure we are basing the adaptation logic on the right criteria and, as a result, also altering the correct elements.

Selecting the Right Adaptation Inputs

In traditional settings, input may include personality measures, assessments of prior knowledge, learning style performance, or aptitude tests (Landsberg et al., 2012). For example, if the goal is to measure cognitive workload, an adaptive simulation would require measurement of cognitive activity utilizing live sensor technology such as an

Electoencephalogram (EEG) (Dey et al., 2019). Therefore, we must start with identifying inputs that serve the training goals. An adaptive training that aims to improve performance and time on a procedural task, such as surgery or assembly tasks, will require different inputs compared to adaptive training that aims to challenge and reduce training time, such as memorization trainers. Surgery trainers may aim for training mastery, and as a result, inputs may require many aspects of performance such as accuracy, time to complete task, and skill decay—with very few inputs related to individual demographics. On the other hand, memorization trainer inputs may focus primarily on demographic inputs, such as age, previous knowledge, and personality traits. Many instructional designers or stakeholders may desire adaptive training systems to make training difficult and stressful, similar to roles of the trainee during their mission. However, these systems may only be designed around performance metrics and increase in difficulty once a performance ceiling has been reached. If we want to ensure the training remains stressful for the trainee, we must have stress metrics incorporated as adaptive inputs as well. Selecting the relevant criteria will maximize training effectiveness.

How Inputs Inform Readiness

A good input measure is not only reliable but also reflective of the construct of interest—which may require multiple metrics (Landsberg et al., 2012). For example, by incorporating not only accuracy on a test but also response time, systems are able to more accurately assess mastery level performance and adapt based on the more comprehensive picture of the learner state (Kellman et al., 2013). Test or knowledge metrics within the training system can also be adaptive within and between trainees by providing different items or test forms to ensure test security while assessing proficiency multiple times (Carey et al., 2010).

In traditional and live instruction, the adaptive component may be determined by instructor ratings. In pilot training, the instructor ratings may determine if a trainee needs remedial instruction or could move on to more difficult procedures. Although this can personalize training content to the individual trainee at a micro-level, it is delayed from the trainee's time of performance and is often limited to adapting only future training lessons instead of during a lesson. The criteria that are chosen to feed the rulesets for adaptation can make or break adaptive training effectiveness. The rationale for the thresholds of adaptation must be sound and accurately reflect differences in trainee performance. Consider common performance metrics. Often it is determined that there is a "good" level of performance, and a "bad" level of performance. We assume that those with good performance are ready for operations or more challenging scenarios, whereas those with bad performance need more training. Consider a pass-fail system. Many adaptive systems take a singular performance score that, if reached, allows the user to move to more challenging content. An assessment of expert level performance will be necessary for determining appropriate thresholds. Performance metrics utilizing test questions or a score system often have maximum and minimum possible values. Instructor sheets and behavior ranking tools also have limits. Should a trainee who barely met the threshold receive the same next training content as the trainee who scored perfectly? No. As adaptive training is advanced with modern technology, modeling, and AI, the level of content adaptation must shift from rigid rule sets to fluid and subtle changes.

Adaptation inputs also challenge *what* we consider good performance. If a medical trainee is practicing suture techniques, we may have specific criteria for a passing grade. It may simply be memorizing the different closure techniques and when one is superior to others. Does that make them proficient and ready to move to operations? No. Consider a simulated or live suturing exercise. Which trainees would be considered ready for operations? (a) the trainee that managed to complete one stitch per minute with low stress and high skewness in the stitches? (b) the trainee that managed to complete one stitch per minute, with high stress and shaky hands and low skewness in stitches? Or (c) the trainee that managed to complete one stitch per five minutes with low stress and low skewness. If only one performance metric was utilized, our proficiency assessments would lack the full picture for battlefield emergency care readiness. When building adaptive simulators, we must consider the full scope of the key criteria to ensure we are leveraging the maximum benefits of adaptive training. Additionally, by capturing performance along with trainee states and accuracy metrics, the *way* the training content is adapted is also improved. Trainee A could receive scenarios aimed at perfecting technique in a range of abnormal scenarios. Trainee B could be given scenarios aimed at increasing the stress tolerance in those scenarios or self-directed training to practice as much as desired to increase confidence. Trainee C could receive similar scenarios with individualized goals to reduce time-to-complete. The *inputs* to adaptation ensure we reach the optimal *outputs* of training.

Designing Adaptive Logic

Shute and Zapata (2012) describe different modeling approaches to build adaptive rulesets that determine how the future training content will be altered. Approaches can use a set of preset information about the trainee or expert that are then referenced to determine the best training content. Examples of these include (a) stereotyping methods that collect characteristics about the trainee and make assumptions about the best level to start a trainee at and then individualizing based on performance, (b) developing an expert model and comparing the trainee's performance against an expert profile, and (c) persistent student models that collect information on the trainee's history and adapt over time relative to their long-term training profile. The difficulty with approaches that have pre-defined plans are ensuring accuracy, as ill-defined plans could lead to ineffective adaptive plans. Other types of adaptation logic can focus more-so on predictive modeling with more emphasis on data prediction of performance as opposed to the content plan. These can include (a) machine learning models that are able to more accurately classify the learner, making the adaptive training logic more effective, (b) Bayesian networks that provide the opportunity to leverage probabilistic relationships to determine the best course of action, (c) plan recognition models that determine best training plan based on previous actions, and (d) cognitive models that determine and predict the state of knowledge of the trainee and provide content aimed at filling the knowledge gaps. The quantitative and data driven approaches of these methods could provide greater accuracy in adaptive learning over instructor-driven approaches. However, they require datasets to drive the initial models and validate them. The best approach is dependent on the capabilities of the training programs and the resources available to invest in the training.

As we consider the number of inputs argument previously discussed, the inputs into the data-driven approaches can exponentially increase the required data to accurately model learner behavior. Additionally, considerations should be given to the costs associated with determining the number of potential outcomes of adaptation logic dependent on the number of inputs. Consider a simple rule set to either make the next training scenario easier, harder, or the same. With two performance inputs of "good" or "poor" classifications, you have a matrix of four potential performance states with a need to determine whether the next scenario will be easier, harder or the same for each outcome. However, as you increase to three or four inputs into the adaptation logic, the matrix increases to eight potential states and sixteen potential states respectively. If the adaptive training has the potential to adapt different aspects of the training, the logic becomes even more complex.

SIMULATION & GAME-BASED ADAPTIVE SYSTEMS

Unfortunately, adaptive systems require some level of initial evaluation to ensure that the adaptation scheme is accurately and effectively adapting the way we intended (Kellman, 2013). Utilizing commercial-off-the-shelf systems and game-based development software, simulated training can be developed by novice developers at low costs and with rapid timelines (Rebensky et al., 2020). Compared to live or macro-level adaptation, game-based development systems, such as Unreal Engine and Unity, allow for rapid updates to potential adaptation approaches that can be refined through testing. In addition, these game engines have various features to support development with non-experts. Simulators can also take in subjective survey data to estimate knowledge or personality traits. Research in adaptive strategies has demonstrated the impact of specific personalities on the effectiveness of different approaches to adaptation (Bauer et al., 2012). For example, those in high openness may be trained effectively in simulations that increase and decrease in difficulty. Integrated with surveys such as Qualtrics, connection with external systems, and data logging with storage, game development engines can support a wide variety of adaptive strategy approaches. Relative to adaptation logic, simulation or game-based training allows collection of various metrics, construction of a database of potential training scenarios, and connection with outside models or agents that can guide the adaptive training logic. Rule-based logic can be used in the early stages of the adaptive simulator with data collection occurring in the backend of the simulated environment. The collected data could then be used to feed data-driven models that can be refined and validated and plugged into the simulator down the line. This approach serves as an adaptive training design while keeping initial investment low. As a result, game engines have become a popular option for developing adaptive training technologies. The following section will describe some novel designs along with open areas and limitations of these systems.

Research by Dey et al. (2019) incorporated EEG systems within Unity to enable adaptive task difficulty based upon cognitive workload. At the beginning of the experiment, by utilizing the n-back—a working memory task—at 1-back and 2-back levels, the simulation was able to assess a trainee's EEG activity during easy and difficult tasking. Then, participants engaged in an object search task with varying levels of difficulty. The adaptation approach of this system was the dynamic style, which aimed to keep participants within an optimal level of cognitive workload. The goal of the effort was to train cognitive functioning. The study results indicated an effective adaptive simulator that was able to keep the participants' cognitive workload within an ideal range without decrements to task performance. However, while the task utilized within this training study is popular amongst EEG studies, its relevancy or transferability to real-world cognitive tasks is unclear. A low relevancy to live operations is a common limitation of adaptive simulators (Sottilare, 2015). As a result, more adaptive systems are needed with relevant use cases. Additionally, the authors note that the cognitive metrics utilized were not comprehensive in nature. The range of task difficulty and utilizing only response time as a metric for task performance were also noted as limitations. This study demonstrated the capability of developing an adaptive simulator based on live physiological data, but the application to military training and the relevant inputs, outputs, and assessment metrics are still unclear.

Game-Based Approach for Iterative Adaptive Design & Research

Game-based development software has the potential to improve the current state of adaptive training. To advocate for the possibility of building upon the breadth of adaptive training research while also addressing the limitations presented above, we describe a potential use case—a driving simulator. Through this use case we will describe and break down an approach to designing a game-based adaptive system (see Figure 2).

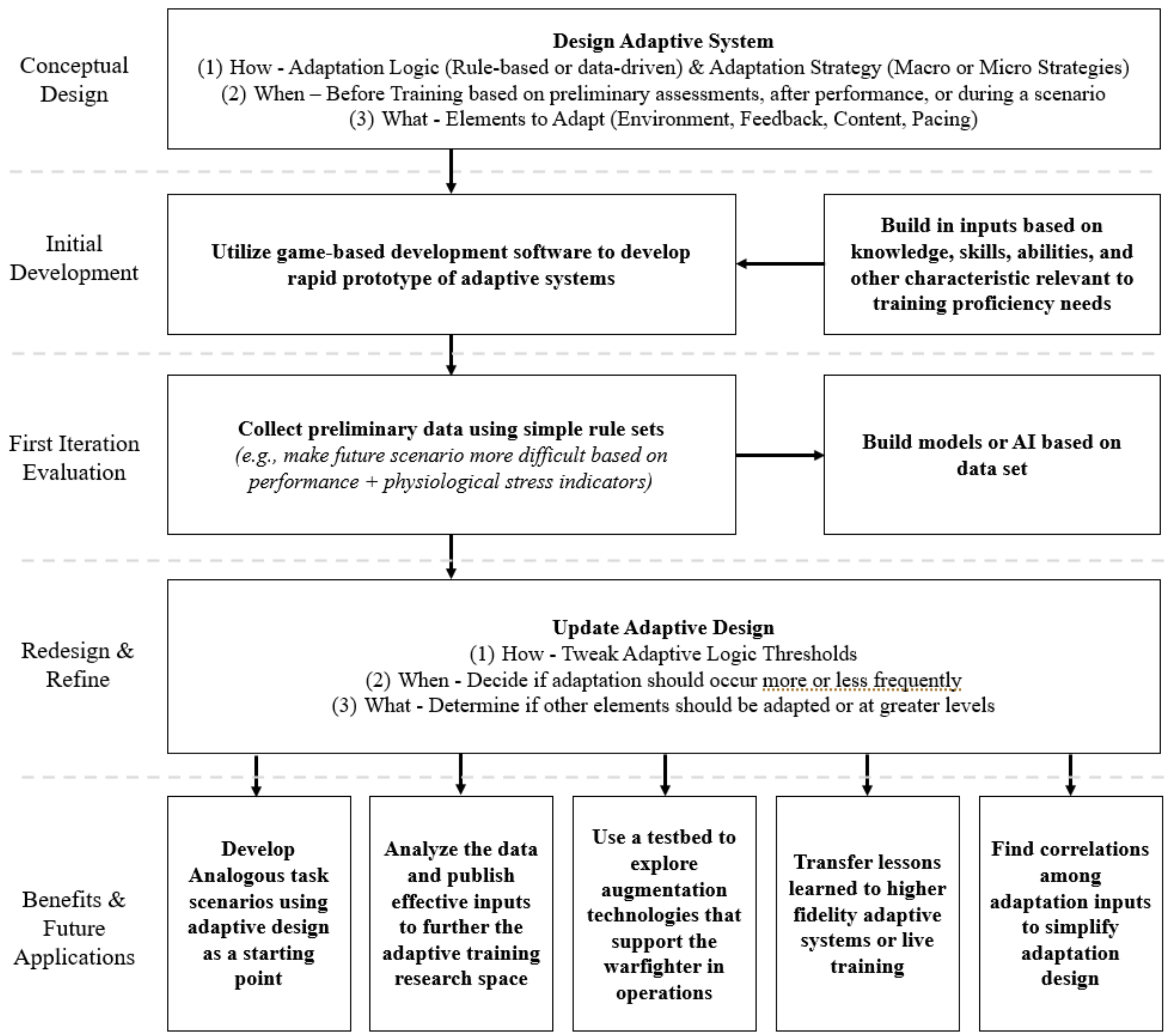

Figure 2. Game-Based Adaptive System Design Approach

Driving tasks could have commercial as well as military applications along with many other operational tasks that require systems monitoring and multi-tasking such as remote pilot operations and manned pilot operations. Identifying the key KSAOs of an operational task allows one to develop a simulator that builds adaptive systems that could be applicable to other domains. The largest type of adaptive systems that exist are ones that allow adaptation between scenarios, but, with game-based training, we can adapt the training to respond *during* a scenario. Based upon the adaptation inputs, many elements can be altered during a driving scenario for *when* to adapt. If the training aims to increase challenge and improve maneuvering skills, game-based development software can procedurally generate roads ahead to be more difficult and curvier to navigate. If the training aims to improve reaction time in off-nominal events, obstructions in the road can be triggered ahead or the behavior of other vehicles on the roads can be adjusted to be more aggressive. Games, such as *Grand Theft Auto* or *Hello Neighbor* that scale the difficulty, provide more aggressive AI, or respond differently based on the actions of the player, can be used as guidance for ways of *how* to adapt a training environment as a result of the individual trainee performance. The important aspect is mapping *what* (or the elements that change within the training environment) facilitates changes in our inputs that allows the adaptive training to determine if the KSAOs end-goals are improving. For example, ensuring that making scenarios more difficult by making enemies more skilled (what*)* actually leads to changes in our performance metrics or stress metrics (adaptive system inputs) that allow us to determine if a trainee can perform under stressful situations against adversaries (KSAOs; conceptual design phase of Figure 2). Initial rule sets can then be established for exactly at what levels of performance or trainee state that the roads may render more curved, or that other drivers begin to merge in front of the trainee's vehicle (Initial development phase of Figure 2).

An adaptive simulation design within game-based development software has the ability to collect and store a variety of data. The data collected throughout adaptive training can be utilized to continue to improve adaptive systems and training and further improve training effectiveness or reduce costs (Sottilare, 2015). Driving tasks allow for a wide variety of performance metrics that can be leveraged, including center line deviation, velocity standard deviation, response time, and compliance with road regulations. Physiological metrics can also be captured, including heart rate, galvanic skin response, as well as eye tracking, to determine scan patterns and distractions. Although early designs of a driving simulator could adapt based upon a set of selected adaptation criteria, collection of other performance data will allow the exploration of other adaptation inputs and thresholds (First iteration evaluation phase of Figure 2). An initial rule set may use time to complete a route as a performance metric, but ultimately find that the variance in velocity during the scenario is a better predictor of driving proficiency. Due to the heavy cost associated with calibrating an adaptive simulator or building a machine learning based adaptive algorithm, game-based adaptive systems can be self-improving as well as serve future adaptive systems using the body of collected data with simple rule-based adaptive strategies. The data collected from the initial sessions can be used to improve the thresholds or inputs used to feed what and *when* to adapt. Other elements of the scenario may be more effective at training, or training adaptations may need to occur more or less frequently. The data can also then be used to train data-driven models that are more robust than strict rule sets that determine when to adapt. These models could make adaptive training strategies more accurate and beneficial for training (redesign and refine phase of Figure 2).

Benefits of a Game-Based Approach for Adaptive System Design

Many benefits follow the initial design of an adaptive system as outlined in Figure 2. An adaptive driving simulator could also help to address the issue of transfer of training. Many current adaptive systems lack relevancy to operations (Sottilare, 2015; Dey et al., 2019). In addition to driving tasks, trainees could also be given a cognitive task. Secondary tasks in operations could be following directions, engaging in a phone call, or in military operations maintaining comms with other units or monitoring system states. Within simulators, trainees could be given commonly used experimental tasks as well as applied tasks. For example, a secondary task used in driving research is the n-back task in which trainees must detect patterns in a series of letters. Trainees could be given the n-back task and then subsequently a more operationally relevant task such as monitoring and responding to communications. In each scenario, the same general structure is utilized—inputs are based on primary driving performance, cognitive task performance, and physiological state. As a result, different tasks can be simulated and fed into the same rule-based combination. The results are two-fold. One, the communications task can be compared to the experimental n-back task to validate that the operationally relevant tasking elicits similar changes in the trainee's state and performance when compared to validated cognitive tasks. Second, the training design allows and demonstrates that the same general adaptive framework can apply to similar domains. Designing adaptive systems with this approach will assist in reducing development costs as similar tasks are added. For example, the same adaptation framework could be applied to flight simulators, remotely piloted vehicles, and other similar operational domains. Each requires controlling a vehicle, attending to system states, and engaging in operational communications, and can quickly become a high workload task. As a result, building a framework in one domain and using similar computational approaches (in this case, a simple rule-based simulator using averages as adaptation thresholds) can be applied to other future use cases potentially reducing development costs.

Outside of the adaptive training itself, low-cost game-based adaptive systems afford many other testbed potentials. Once data has been collected using the simple version of the adaptive training, the opportunities open. The data can be used to train AI to build a more robust adaptive logic system. Then, the AI can be substituted for the rule-based adaptation and the two can be compared to better inform adaptive systems research. The adaptation strategies can also be refined and iterated in the low-cost system and then implemented in higher fidelity, live, or more complex systems that would be too expensive to iterate within. The adaptive system can also be used to experiment with augmentation approaches or technologies and determine the resulting impacts on performance and workload when triggered at key stages of the training. As all the data to assess new augmentations are already being captured by the system, it fits naturally as a means to test potential new technologies such as a Heads-Up Display (HUD) or other Augmented Reality (AR) situation awareness tools. Finally, the input metrics can be assessed as accurate or viable means for adaptation. By capturing a myriad of performance, individual characteristic, and state-based measures, we can assess if there are potential better metrics to be utilized. For example, time-based performance metrics may not be robust enough to indicate high workload, but the data collected by the systems can be analyzed after some data collection and determine if better metrics should be inserted into the adaptive logic. Considering that there are instances in which we may be unable to capture certain metrics, such as physiological measures, inputs can be compared against one another to determine any potential correlation. If it is found that accuracy-based performance metrics correlate highly with heart rate metrics, in that particular use case it may allow the reduction of the adaptation logic complexity. Adaptive logic models with and without high-cost inputs can be compared and a value-cost determination can be made. Adaptive simulators can become the norm and more effective by leveraging all the capabilities of game-based development systems relative to data collection and rapid environment manipulation. As a low-cost development and iterative research testbed, some of the costs of adaptive systems can be reduced and changed rapidly on pace with the change of the modern battlespace (see Figure 2 for a summary of design approach).

CONCLUSION

Adaptive training has been around in many forms in both traditional and simulation settings. Within more advanced data collection and simulation technology, the capabilities for adapting content are greater than ever. Adaptive strategies can focus on tailoring content to a group or at the individual level. Instructional designers can choose *when* to adapt at either the beginning of training or during with variations in adapting once or many times. Instructional designers can choose *how* to adapt including the content such as future lessons or elements within the environment, increasing or dynamic difficulty levels, utilizing rule- or data-based logic. Instruction designer can choose *what* to adapt such as feedback presented, the difficulty of environmental elements, or scenarios that target specific KSAOs. However, constraints of the inputs feasible within the system and the cost of these strategies should be considered. Adaptive training can be a costly investment, and as a result, we presented a game-based adaptive system approach that could serve as streamlined and low-cost approaches to developing and refining adaptive systems that further current and future adaptive system testbeds. By using an iterative approach that leverages the data capabilities and rapid prototyping capabilities within simulation, designers can build a robust adaptive training system.

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