Augmented Intelligence for Instructional Systems in Simulation-based Training

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Abstract. Augmented Intelligence is a design pattern for a human-centered collaboration model of people and artificial intelligence (AI), where machines assist humans in tasks such as data analysis, information retrieval, decision-making, and task execution. In this study, the concept of Augmented Intelligence is applied within the context of an instructional system for simulation-based training. Here, the collaboration between human and machine is focused on the role of the instructor, which is to guide the learning process of one or more trainees toward some learning objective. We identify different levels of machine support to assist an instructor in this role during an adaptive training cycle. Additionally, two design aspects are discussed that contribute to increased levels of intelligence, namely the challenge of domain alignment to empower automation capabilities, and the benefits of simulation-based task environments to deliver AI-enabled approaches. Examples are discussed in the context of military training.

Keywords: Augmented Intelligence, Instructional system, Simulation, Training

1 Introduction

Simulation-based training is increasingly used as a method for training professionals on skills, abilities, and competencies in domains such as the military, aviation, or healthcare. Simulated task environments offer an interactive learning environment for trainees to experience representative real-world scenarios, while commonly being more cost-effective compared to live training. As in live training, simulation-based training is often instructor-led and supervised, where instructors prepare training scenarios, observe and assess trainee performance during training, provide feedback, and plan follow-up training needs and activities.

In current practice, instructors have little technological support for guiding simulation-based training processes. However, the increasing demand for data-driven, personalized and adaptive training has yielded promising research on supportive instructional technologies in areas such as learning analytics, human performance modelling, recommendation algorithms, and scenario generation. Fully automated approaches for adaptive training, such as Adaptive Instructional Systems (AIS), exclude the need for an instructor. However, these are often a bridge too far when considering complex domains such as military training, which regularly involves learning complex knowledge, skills and abilities in dynamic task environments. The role of the human instructor cannot easily be disregarded as it brings rich knowledge about the task domain, individual learners, and instructional strategies that can be complex to model. Also, subjective insights may be based on years of experience, and an objective truth of ‘adequate’ trainee performance may not always be quantifiable by a machine. In this view, intermediate approaches seem more feasible, wherein machines support instructors for some instructional processes, while instructors retain control over others. In this paper we explore such different forms of instructional support using the concept of Augmented Intelligence.

Augmented Intelligence is “a design pattern for a human-centered partnership model of people and artificial intelligence (AI) working together to enhance cognitive performance, including learning, decision-making and new experiences.” [1]. As a human-centered design, it aims to play an assistive role, combining strengths of both human and machine, while enhancing human intelligence rather than replacing it [2]. When applied to the context of instructor-led training, Augmented Intelligence can be used as a design pattern for implementing intelligent instructional systems to assist human instructors in their observation, assessment, decision-making, and task execution during adaptive training.

This paper presents a design pattern for developing Augmented Intelligence for instructional systems in the context of simulation-based training. The approach is based on progressive levels of machine support that can be considered for implementing an instructional system, illustrating some of the challenges for automation, as well as benefits for a human instructor. In addition, two design perspectives are highlighted that contribute to increased levels of intelligence. The first one addresses the problem of domain alignment, which relates to the grounding of (instructional) knowledge, required to tailor machine algorithms to operate in a particular task domain. The second one addresses the role of simulation-based task environments to enable AI approaches for enhanced machine support in instructional systems. Through advances in AI technologies and the need for data-driven solutions, (human-in-the-loop) simulations can play a central role in data provision and delivering AI-based approaches. Finally, we conclude the paper by summarizing the ideas presented with a future outlook.

2 Levels of Machine Support

In an instructional system, the role of an instructor is to guide the learning process of one or more trainees by tailoring instruction to optimize learning in the context of some learning objective. In the view of Augmented Intelligence, we consider the fulfillment of this role as a collaborative effort between human and machine, where the machine supports the human in its task. This concept is visualized in Fig. 1. In the figure, five levels of machine support are identified within an adaptive training cycle. These levels correspond to an instructor’s ability to observe, measure and assess trainee performance, develop instructional plans, and instigate these through adaptations of the task environment.

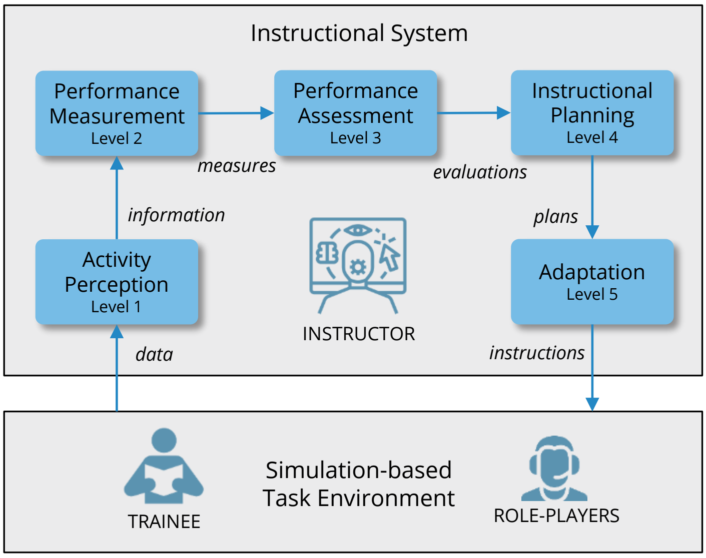

Fig. 1. Augmented Intelligence for an instructor role in an adaptive training cycle, conceptualized through different levels of machine support[1]

A collaborative execution of the adaptive training process is shaped by a division of labor between the human instructor and the machine. The level of machine support is considered to be flexible, depending on the application. At one end, the machine provides no support and the instructor performs all levels by itself. At the other end, the machine performs all levels and the instructor would be out of the loop, in which case the machine acts as a true AIS. In between these extremes, the machine provides support for one or more levels, and communicates its results through some human machine interface (such as a dashboard or instructor operating station). The instructor can combine objective data obtained from automated processes with its own subject insights to implement remaining levels. Below we first describe each level in more detail, followed by an outline of illustrative related work.

2.1 Levels of Support

Level 1: Activity perception. At this level, the machine is able to observe the training environment and the trainee's behaviors and activities in that environment. By translating data that can be acquired from the simulation into meaningful, semantic information associated with the task domain, the human instructor can be supported in building situation awareness. When the machine can monitor distinct training tasks or activities as they are being performed, it enables the instructor to observe *what* tasks the trainee is undertaking, such that it can concentrate on relevant measurements to determine *how* the trainee is performing on those tasks.

[1] Note that the instructor role could also be seen as being fulfilled by the trainee itself, hereby suggesting self-guided training, as opposed to instructor-led training.

Level 2: Performance measurement. At this level, the machine is able to extract and compute relevant performance metrics from the observed data. These metrics serve as quantifiable measures or indicators of task performance, required for consequent evaluation of trainee performance. Through the provision of such objective data, the human instructor can acquire data-driven insights that it can use as actionable information for making informed decisions: it can combine these insights with its own subjective insights in order to form of overall performance assessment.

Level 3: Performance assessment. At this level, the machine is able to assess and evaluate a trainee's performance on a task, based on some performance standard as a reference. A performance standard is an objective, predetermined notion of proficiency for a task that a trainee is expected to achieve. It can be represented by certain criteria, thresholds, or expert models of performance that can be used as a benchmark for comparison. An assessment is then the result of a comparison between measured performance and the performance standard. Objective assessments can be used by the human instructor (possibly augmented with its own subjective assessments) to update learner profiles, refine training needs, and plan instructional activities.

Level 4: Instructional planning. At this level, the machine is able to plan instructional activities, based on a trainee's assessed progression towards some learning objective. Instructional plans may relate to follow-up training schedules or scenarios, or to in-session adaptations such as direct interventions (e.g. scaffolding or feedback strategies to guide learning) or indirect interventions (e.g. change task complexity through environment adaptations). Personalized strategies may be used that take into account aspects such as learning preferences or measured learner engagement. Machine-based instructional plans can be used by the human instructor as recommendations or decision support on when and how to adapt training.

Level 5: Adaptation. At this level, the machine is able to realize instructional plans through instructions that configure, modify or interact with the training environment. In simulation-based training, this includes for instance the ability to generate or configure new training scenarios, to adapt the behavior of possible virtual role-players, or to provide direct feedback to the trainee. The human instructor can be provided with appropriate control interfaces to realize such changes in the training environment.

2.2 Related Work

Throughout all levels of support, increased technological progress is seen for automated approaches, driven by the increased demand for more data-driven, personalized, and adaptive training solutions. Simulation-based training is particularly suited as it provides a training environment that can be effectively created, observed, and controlled. However, fully end-to-end systems like AISs are still rare in simulation-based training, especially in complex domains such as military training. In this domain, related research and technology are more often dedicated to individual levels of support. Below, we touch upon related research in this context for illustrative purposes.

To support perception at *Level 1*, military standards such as Distributed Interactive Simulation (DIS) have been developed to represent raw simulation data as real-time, domain-specific information about military entities and events in a simulation environment [3]. Additionally, standards such as the Experience API (xAPI) have been utilized in simulation-based training to infer trainee activities from synthetic environments [4]. In line with activity recognition, model tracing techniques have been proposed to track activities and contexts in real-time, based on known hierarchical task models of the trainee [5], hereby enabling context-based measurements at *Level 2*.

Performance measurement at *Level 2* is a well-addressed topic. Specifically for simulation-based training, a systematic review of methodologies and best practices for computer-assisted performance measurement is provided in [6]. In specific domains such as fighter pilot training, performance measurement has been extensively researched to measure technical and non-technical skills, including task proficiency, teamwork, communication and situation awareness [7, 8]. Within this domain, measurement tools such as PETS [9] provide a framework to develop and deliver performance metrics, and has been used e.g. to support subject matter experts in evaluating training effectiveness [10] or to assess AI pilots to support training [11].

Closely related in research is performance assessment at *Level 3*, which can be automated when some 'absolute' measure of desired performance can be known. It is often recognized that fully automated assessment is not feasible in many domains and that human judgement cannot easily be replaced, giving rise to partial automation or assessment aids. Though, several studies on automated assessment exist. For instance, in [12], a system was evaluated that assessed performance based on observed examples of good and bad performance in tactical air engagement scenarios, showing a high degree of agreement with a human grader; and in [13], an automated assessment method for training simulators was investigated where assessment rules are learned from observing experts and students performing training tasks. A broad review on systems and trends for automated after action review in military training is given in [14].

After assessments are made, instructional planning at *Level 4* caters the planning of teaching activities for follow-up training or in-session interventions. For instance, in [15], methods are explored to tailor personalized training programs for maintaining currency, based on measured or predicted skill decay; in [16], a recommendation system has been proposed that recommends optimal training tasks based on training needs and measured trainee competency levels; and in [17], real-time difficulty adjustments are implemented through the adjustment of AI opponent behavior, based on measured trainee proficiency.

Finally, for adaptation at *Level 5*, (semi-)automated approaches have been explored to relieve instructors from the often resource intensive manual activity of scenario construction. For instance, in [18], generative techniques are leveraged to generate training scenarios aligned with learning objectives and individual learner characteristics; whereas in [19], semi-automated methods are used that allow an instructor to direct the generation process to reflect its own preferences. Implementing adaptive strategies are strongly guided by instructional design principles on how, when and what to adapt [20].

2.3 Concluding

The identification of different levels of machine support presented in this section guides the design of increased automation while considering the human role in the process. The levels of support that can be provided for a particular application depends not only on the available technology and algorithms to fulfill particular levels but also on the ability to the capture required domain and instructional knowledge associated with those levels in machine language. For instance, a fully automated instructional system requires a machine understanding of the task domain, instructional needs and means throughout the system. In the next section, we discuss this challenge. Finally, a successful deployment lies in the trustworthiness of the system to provide validated automated aids, as well as the human instructor's acceptance of and trust in the system.

3 Domain Alignment

In the previous section, different levels of machine support were identified for an adaptive training process. One of the challenges for implementing increased levels of support is the tailoring and alignment of machine algorithms to operate in a particular (instructional) task domain. This is also known as *domain alignment* and is the process of adapting or tailoring algorithms to perform well on a specific domain or task. For an instructional system, this relates to the problem of how to incorporate, ground, and align domain knowledge throughout the system, such that algorithms can be semantically aligned across the processes of an adaptive training cycle. The domain alignment problem for an adaptive training process is shown in **Error! Reference source not found.**. In the figure, domain alignment is conceptualized through top-down requirement drivers for domain-specific knowledge that is needed to implement different levels of support. This is explained using an example below, where the different knowledge concepts are shown in italic.

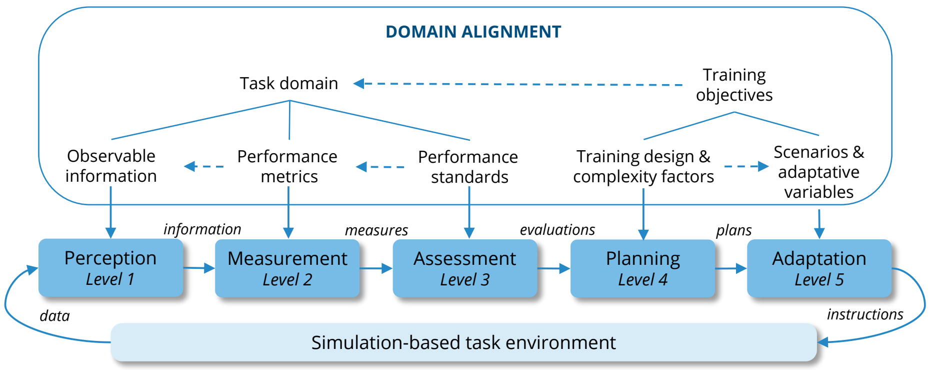

Fig. 2. Domain alignment in an adaptive training process. The solid arrows represent information flows; the dashed arrows represent top-down requirement drivers.

3.1 An Example

Consider a competency-based training for a fighter pilot, designed to train specific technical or non-technical skills through whole-task or part-task training (e.g. specific mission types or tactical engagements). The *training objectives* specify a set of competencies or skills that can be trained through different training tasks in a simulated environment. Job-specific competencies, skills and tasks may originate from a pilot's competency profile or training needs analysis. The training objectives drive the scope of the *task domain*, which encompasses the (expert) knowledge about the tasks to be trained. These are the tasks that (1) trainees should have the opportunity to master during training, and (2) instructors should be able to observe, measure and assess. The ability to assess a training task requires a *performance standard* as a reference of desired performance. Associated are *performance metrics* that should be measurable to compare against this standard. These, in turn, drive requirements for the kind of *information* that should be observable from the simulation data in order to compute them.

When the trainee has been assessed on a task and has shown sufficient mastery, the *training design* may be updated to prioritize other training tasks for follow-up training. Alternatively, the same task may be trained but different *complexity*. The training design drives the requirements for the kind of *scenarios* that should be supported in the simulated task environment for the trainee to experience. The need for in-session adaptations further drives the requirements for *adaptive variables* to be supported.

The example illustrates two key aspects of domain alignment. First, it shows how requirements for domain knowledge can be derived from a top-down analysis, starting from instructional objectives, all the way down to what is needed from a simulation environment in terms of data acquisition, scenario elements, and adaptation options. Second, it shows the dependencies between knowledge concepts across different levels of support. When these concepts can be computationally grounded and interconnected, this promotes alignment between supporting algorithms throughout the system.

3.2 Approaches

Related work that involves domain alignment can be distinguished between bottom-up and top-down oriented approaches. Bottom-up approaches focus more on data strategies, infrastructures, architectures, standards, and tools to manage, represent, and communicate domain-related knowledge within learning ecosystems. For instance, in [21], the authors discuss the need for data-driven learning analytics and explore architectures and infrastructures for data management that help organizations transform performance data into actionable insights. Further, data strategies have been proposed that focus on standards to promote uniform integration of learning technologies. For instance, ADL's Total Learning Architecture (TLA) defines data standards for concepts such as observable activity data from learners; training session meta-data; competency definitions; and learner profiles [22]. Finally, standardization efforts are undertaken within the AIS community on the definition and interoperability of components in an AIS system, including components to manage domain knowledge, track learner data, plan instruction, and provide user interfaces [23, 24]. Such initiatives are supported by frameworks such as GIFT that provide tools, methods, and standards for developing AISs [25].

Top-down approaches focus more on the collaborative process between instructional designers and engineers on how to model instructional design concepts. For instance, the need for a human-centered design approach is argued to orchestrate so-called actionable learning analytics [26]. It focuses on three principles, namely (1) the use of learning design to derive needs for algorithmic learning analytic (LA) solutions, (2) grounding educational theories in LA solutions, and (3) facilitating stakeholder involvement in the design process to reflect the needs and values of instructors and trainees. Advances in AI technologies also benefit human-centered approaches. For instance, large language models (LLM) can play a role in knowledge acquisition, elicitation and organization of acquired knowledge in computational forms [27]. Further, their potential is reviewed to support personalization and teacher activities related to generating automatic feedback, personalized learning tasks, learning content (such as scenarios), and recommenders [28].

In conclusion, effective domain alignment empowers automation capabilities in instructional systems. The grounding of domain-specific knowledge and its semantic alignment throughout the system not only requires suitable data strategies and infrastructures, but also necessitates a collaborative effort between instructional designers and engineers, matching instructional needs with technological solutions.

4 Simulation-based Task Environments

Simulation-based training can deliver tailored training programs for trainees in specific task domains. Compared to live task environments, simulated task environments offer several benefits for leveraging AI-enabled approaches in instructional systems, particularly for developing learner models of performance and expert models of behaviors. **Error! Reference source not found.** illustrates this notion.

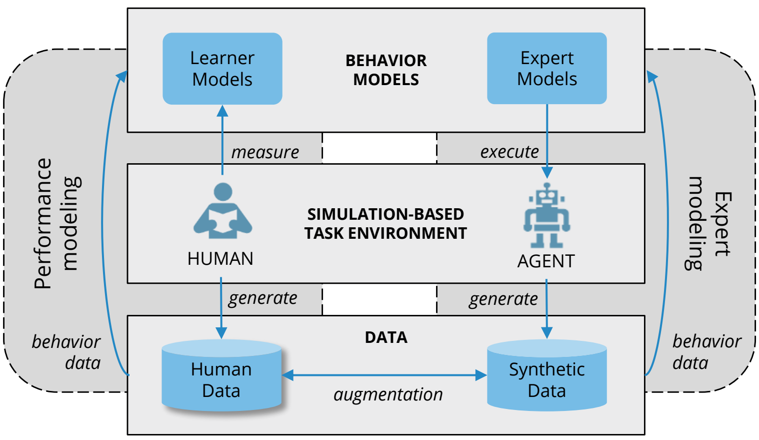

Fig. 3. Behavior models in a mixed human-agent, simulation-based task environment.

In the figure, the simulation environment is shown as a mixed human-agent environment that can be populated with human actors and agent actors. For human actors (e.g. trainees), human-in-the-loop simulations can effectively measure and capture learner data, which is needed to develop human learner models of performance. For agent actors, simulations can be used to learn and deploy expert models of behaviors for various purposes (as will be described). For both type of actors, the simulation mediates in the generation of behavior data, where this data can consequently be used for data-driven AI approaches in the development of either learner or expert models. Below, we elaborate on these principles, referencing illustrative related research.

4.1 Learner Models of Performance

Human performance models are used in instructional systems to measure, track or predict skill development of learners over time. Human-in-the-loop simulations can acquire the learner data required to develop such (personalized) models. To give some examples, in [29], learner data is collected from trainees across a series of team training sessions in order to measure team performance progression over time. Bayesian inference is used to propagate measures from domain-specific performance metrics to higher-level teamwork competencies. In [15], learner data is collected to develop a predictive model of skill decay, which is used for time-based scheduling of future training sessions to maintain personnel currency of complex skills. In related research, agents are used to simulate human learning on a task. The envisioned application was to employ simulated learners to computationally derive an optimal part-task training design for humans on the task [30].

4.2 Expert Models of Behavior

Expert models in simulation-based task environments represent computational models of performance. Traditionally expert models have often been hand-crafted using rule-based techniques. More recently, through advances in areas such as deep reinforcement learning, expert behaviors can also be learned by agents in complex task environments [31]. Expert models of behavior are used for a variety of purposes in instructional systems. For instance, in [32], expert models of fighter pilot behaviors are trained using reinforcement learning from human feedback (RLHF), where tacit expert preferences are encoded in human-readable form and used for automated assessment or demonstration learning. Alternatively, expert models are used to represent embodied agents as virtual role-players. For instance, in [33], agents are trained to support adaptive team training and influence learning engagement in simulation-based training. Embodied agents can also assume a tutoring role, exhibiting teaching activities such as through prompting or using other social learning methods [34].

4.3 The Role of Data

To support the development of data-driven AI approaches for behavior models, such as described above, the simulation plays a central role in collecting and generating (learner) behavior data. The simulation can be agnostic to whether such data is generated by human actors or agent actors. Regarding human learner data, an issue often faced is that the amount of (historical) data that can be obtained from regular training sessions is insufficient for training AI algorithms. To address this, researchers have resorted to alternative approaches. One approach is an organizational one that focuses on human data collection strategies. This includes, for instance, the organization of dedicated data collection sessions with students or experts [35], or outsourcing to a broader audience using (semi-)public online (serious) games to harvest player behaviors [15]. An alternative approach is a technological one and uses synthetic data to address the data scarcity problem. For instance, data augmentation methods have been developed to generate new representative behavior data from limited human data samples [36, 37]. Backwards, synthetic agents have been used to generate synthetic data as representative human data, for instance to investigate data-driven behaviour modelling for demonstration learning [38], or to develop activity recognition algorithms for human behaviors [39].

In conclusion, it is seen that simulation-based task environments enable the development of data-driven AI approaches, mediating in human data collection, synthetic data generation, and providing interactive machine learning environments. Their role in supporting performance modelling and embodied tutoring in simulation-based training further empowers automation capabilities in instructional systems.

5 Conclusion

In this paper, we positioned the concept of Augmented Intelligence for instructional systems as a design pattern for increased instructor support through automation in simulation-based training. We started by identifying different levels of machine intelligence to support the role of an instructor during an adaptive training cycle. These levels range from more low-level support, such as measuring trainee performance and adapting the task environment, to more high-level support, such as performance assessment and planning instructional action, in correspondence to training objectives. The design pattern provides guidance on implementing increased levels of support while recognizing the human role in the process.

Next, we discussed two design perspectives that foster increased levels of support. The first one highlights the need for effective domain alignment, relating to the grounding of domain knowledge to allow machine understanding of the task domain and instructional needs. Key is an alignment of bottom-up approaches that lay the infrastructural foundation for managing knowledge throughout the system, with top-down approaches that focus on the role of instructional designers in the design process.

The second perspective highlights the role of simulation-based task environments to drive AI-enabled approaches for developing behavior models. Human performance models support the measurement or prediction of trainee performance, whereas expert models support training through capabilities of automated assessment, virtual role-players, demonstration learning, or social learning strategies. Simulation-based task environments facilitate AI-based approaches for these models through data collection, data generation, and delivering interactive machine learning environments within the respective task domain.

When projecting on future developments, advances in AI will be instrumental in enhancing Augmented Intelligence for instructional systems. Recent trends in generative AI, large language models, or human-directed reinforcement learning show innovative approaches to cater to effective domain alignment, empowering instructional designers to collaborate in the design process, concerning delivering fit-for-purpose training environments, scenarios, interpretable learning analytics, and personalized instruction. In parallel, continued advances in immersive and digital twin technologies are blurring the line between simulated and real-world task environments, such that instructional aids for simulation-based training will become more aligned with, and accessible to mixed reality training environments.

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