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RESEARCH ON MANAGING GROUPS AND TEAMS
VOLUME 19

BUILDING INTELLIGENT TUTORING SYSTEMS FOR TEAMS: WHAT MATTERS

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emerald
PUBLISHING

United Kingdom – North America – Japan
India – Malaysia – China

Emerald Publishing Limited
Howard House, Wagon Lane, Bingley BD16 1WA, UK

First edition 2018

British Library Cataloguing in Publication Data
A catalogue record for this book is available from the British Library

ISBN: 978-1-78754-474-1 (Print)
ISBN: 978-1-78754-473-4 (Online)
ISBN: 978-1-78754-475-8 (Epub)

ISSN: 1534-0856 (Series)

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INTRODUCTION

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EXAMINING CHALLENGES AND APPROACHES TO BUILDING INTELLIGENT TUTORING SYSTEMS FOR TEAMS

Robert Sottilare and Eduardo Salas

ABSTRACT

This chapter examines some of the challenges and emerging strategies for authoring, distributing, managing, and evaluating Intelligent Tutoring Systems (ITSs) to support computer-based adaptive instruction for teams of learners. Several concepts related to team tutoring are defined along with team processes, and fundamental tutoring concepts are provided including a description of the learning effect model *(LEM), an exemplar describing interaction between learners and ITSs with the goal of realizing optimal tutor decisions. The challenges noted herein are closely related to the LEM and range from acquisition of learner data, synthesis of individual learner and team state models based on available data, and tutor decisions which center on optimizing strategies (recommendations) and tactics (actions) given the state of the learner, the team, and the conditions under which they are being instructed, the environment. Finally, we end this chapter with recommendations on how to use this book to understand and design effective ITSs for teams.*

Keywords: Adaptive instruction; intelligent tutoring systems; learning effect model; team tutors; learning; performance

Building Intelligent Tutoring Systems for Teams: What Matters
Research on Managing Groups and Teams, Volume 19, 3–16

ISSN: 1534-0856/doi:10.1108/S1534-085620180000019001

PURPOSE

The purpose of this chapter is to introduce the concepts, perspectives, and applications needed to fully understand the complex task of building intelligent tutoring systems (ITSs) that deliver and manage effective and efficient adaptive instruction for teams. Our goal is to portray the importance of ITSs as learning tools for teams in order to help readers understand their current and potential future capabilities in various instructional domains and use cases. In support of this goal, we examine historical, current, and emerging approaches for developing ITSs and discuss how we might adapt these concepts, perspectives, and applications to realize intelligent machines that can author, deliver, manage, and evaluate adaptive instruction for team-based tasks.

To convey the mental model of ITSs for teams, we first define concepts and examine team processes (e.g., learning, performance, satisfaction, and viability). Next, we discuss the primary functions of ITSs as they exist now as adaptive instructors for individual tasks, and measures of their effectiveness. Then, we anticipate some of the major challenges to building ITSs for teams and project how ITSs for individual tasks might be adapted to provide effective adaptive team instruction. Finally, we summarize how multidisciplinary teams might use this book as guide for designing and building ITSs for teams. We begin with a few definitions.

CONCEPTS DEFINED

A selected set of definitions related to the adaptive instruction of teams is provided to focus the discussion and concepts that follow throughout the remainder of this volume.

- *Adaptive instruction* – sometimes referred to as *differentiated instruction*; a learning experience tailored to the needs and preferences of each individual learner or team in which strategies (plans for action) and tactics (actions by the tutor) are selected with the aim of optimizing learning, performance, retention, and transfer of skills from the instructional environment to the work or operational environment (Sottilare, 2016).
- *Instructional environments* – any training or educational setting (e.g., physical location, virtual location, or set of conditions) in which the learner interacts with or is immersed within for the purpose of learning (Sottilare, 2016).
- *Intelligent tutoring systems* – a computer-based adaptive instructional system whose goal is to deliver customized, real-time instruction to learners based upon a model of their learning needs and preferences, and usually without human intervention (Psotka, Massey, & Mutter, 1988); computer-based, adaptive instructional applications that interpret learner, team, and

environmental data (usually without human intervention) to select and present content and feedback with the aim of optimizing learning, performance, retention, and transfer of skills (Sottilare, 2016).

- *Learning* – formal (e.g., training or education) and informal (e.g., reading) experiences leading to the acquisition of knowledge and the development of skills (Sottilare, 2016).
- *Operational or work environments* – any work setting (e.g., physical location or set of conditions) in which workers interact with and apply knowledge and skill within for the purpose of making decisions and attempting to complete assigned tasks (Sottilare, 2016).
- *Performance* – the accomplishment or attempted accomplishment of a given action, task, or function as measured against a standard (e.g., quality, accuracy, completeness, cost, and speed); adapted from performance as defined by BusinessDictionary.com (2017).
- *Taskwork* – the development of proficiency in task domains required for a specific duty of one's job (Salas, 2015); taskwork is a domain-dependent learning activity; taskwork may be conducted by individuals or teams.
- *Team* – a group of individuals working together toward a common goal or set of goals.
- *Teamwork* – "coordination, cooperation, and communication among individuals to achieve a shared goal" (Salas, 2015, p. 5); teamwork behaviors are largely domain-independent; teamwork includes the social skills needed to function as a team; teamwork activities may include teambuilding whose goal is to strengthen the coordination, cooperation, communication, coaching, conflict management, cohesion, and collective efficacy of the group (Salas, 2015); teamwork is a necessary prerequisite to satisfactory taskwork performance (Van Berio, 1997).
- *Team satisfaction* – the degree to which members enjoyed being a member of the team (Burke, Sottilare, Johnston, Sinatra, & Salas, 2017).
- *Team viability* – the desire to remain in a group or come back and work/train with same people (Sottilare, Burke, et al., 2017).

TEAM PROCESSES

Teams are the common organizational element in almost every organization. At their simplest, we can relate team performance to two interactive processes: teamwork and taskwork. Salas (2015) defines teamwork as a largely domain-independent process where there exists "coordination, cooperation, and communication among individuals to achieve a shared goal." Taskwork and its associated measures are domain-dependent since the task is focused on learning how to do a specific job. The interaction of team members including their behaviors, attitudes, and shared cognition influence the pace and capacity of their learning, and the effectiveness of their performance (Sottilare, Burke, et al., 2017). According to Hackman and Wageman (2005), team effectiveness is also a function of individual and group level of effort, the development of performance strategies over time, and knowledge and skill brought to the task by each team member. Other team processes may also determine the success of teams over extended periods of time. Team satisfaction can be defined as the degree to which members enjoyed being part of the team, and team viability reflects the degree to which team members exhibit the ability to perform well in future tasks, achieve future goals, and adapt to change.

Whether the instruction is guided by a human tutor or a computer-based tutor, the measures of team learning and performance are complex and dynamic for all but the very simplest tasks. This complexity in identifying markers of shared behaviors, attitudes, and cognition makes the process of choosing the optimal instructional strategy even more difficult. Before we dive into the technical challenges of team tutoring, let's take a step back to examine the fundamentals of tutoring individual learners and later extend these fundamentals to the more complex task of tutoring teams.

FUNDAMENTAL TUTORING CONCEPTS

When we study the interaction between tutor and learner, there are three concepts to be carried forward from human tutoring to machine-based tutoring. While their implementations may be different, they are fundamentally performing the same functions. The first concept is the tutor's knowledge about the learner which is often referred to as the *learner model*. This is the information that the tutor uses to make instructional decisions before, during, and after tutoring experiences. The second concept is the tutor's lesson plan which is the content (e.g., knowledge objects, misconceptions, feedback, media) that the tutor will present to the learner and the sequencing of that content that make up the *domain model*. A third concept is the instructional or *pedagogical model* which includes the tutor's strategies for bringing together the learner and the content to provide a learning experience. Finally, there is the concept of a *tutor–user interface* which enables the learner to interact with the content or the environment delivered by the tutor. Each of these concepts is discussed in terms of their role in adaptive instruction of individuals below.

Fundamental ITS Concepts

The goal of adaptive instruction is to optimize the learning of each individual learner. The interaction of the tutor with the learner and the environment is the basis of effective tutoring experiences. The tutor observes both the learner and the environment and uses this information to select strategies that are likely to enhance their learning. There is uncertainty in this process because the tutor is not able to classify the learner's states with 100% accuracy, and the tutor is not always cognizant of every learner action or change of state in the environment. Dinky, dirty, dynamic, deceptive data (D5; A. Kott, personal communication, February 9, 2017) plays a part in degrading the accuracy and increasing the uncertainty of machine learning classification used by ITSs to determine current and future learner states, and to select optimal instructional strategies and tactics. Machine learning techniques (e.g., Markov Decision Processes) help the tutor manage this uncertainty and allow the tutor to improve continuously through reinforcement learning processes (Mitchell, 1997).

Within the ITS, the interaction between the processes in the learner, domain, and pedagogical models, and the tutor–user interface drive the classification of learner states, which are used to select instructional strategies and tactics in learner-centric systems. The following subsections describe the function of these ITS models along with the role of the tutor–user interface.

Learner Modeling

In machine-based tutors, ITSs, the learner model usually contains the critical information needed for the ITS to estimate the learner's comprehension of objectives within the domain under instruction. According to Sottilare, Graesser, Hu, and Goodwin (2017), the "learner model consists of the cognitive, affective, motivational, and other psychological states that evolve during the course of learning." During adaptive instruction, the learner model stores the information (e.g., learner states and traits) needed to adjust the pace, difficulty, and path of instruction to meet the specific needs and preferences of the learner or the data needed to derive learner states (e.g., emotion or performance) through machine learning or other classification methods. Even at the individual level, a learner model can be multi-dimensional and complex when we think about human variability and all the individual differences that could and do effect learning. Aspiring to tutor at the team level, we multiply the dimensions and complexity by the number of individuals on the team and the critical interactions between members during team tasks.

Domain Modeling

According to Sottilare, Graesser, et al. (2017), the domain model contains "the set of skills, knowledge, and strategies/tactics of the topic" under instruction. The domain model also usually includes an expert or ideal student/learner model along with a set of common principles, bugs, mal-rules, and misconceptions which learners exhibit when training or operating in that domain. Since assessment occurs in the domain model, the ideal learner model is used to compare and contrast the learning and performance of the learner to the learning and performance of an expert. Otherwise, the learner's performance is assessed against some other criteria (e.g., a standard). If we continue to expand our concept of what a domain model is, we might also include external environments that learners interact with or are immersed within. In a physics tutor, the environment is the set of problems presented to the learner. In a medical triage tutor, the environment might be a virtual reality game in which an individual learner practices casualty care on virtual humans. The environment in which the learner develops skills and later applies this learning defines the strategies (plans for action) and tactics (actions) that are possible during instruction and is a critical element of the domain model.

Pedagogical Modeling and Effectiveness Measures

Just as human tutors vary in their pedagogical strategies, ITSs vary in their pedagogical implementation. Some human tutors may rely on trusted instructional strategies to promote metacognitive skills (e.g., question asking, reflective dialog) which enable better habits and enhance learning skills independent of the domain of instruction. Others may depend upon proven strategies like *error-sensitive feedback* where feedback or action by the tutor is triggered by learner errors or *worked examples* where the learner is presented with fully worked example at first which is gradually reduced until the learner works the whole problem. ITSs have adopted and continue to adopt models of successful human tutors. For example, the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, Brawner, Sinatra, & Johnston, 2017) is implementing tutorial planning and metacognitive strategies to enhance the efficiency and effectiveness of tutoring experiences. AutoTutor (Graesser, 2016), a dialogue-based tutor, uses conversational artifacts during reflective dialogs between the ITS and the learner to assess the learner's performance and emotional states. The Cognitive Tutor (Aleven, McLaren, Sewall, & Koedinger, 2006) uses a cognitive model of the task domain to model all the possible paths (successful and unsuccessful) that a learner might take. This requires intimate knowledge of the domain under instruction to provide a working model of the domain.

A variety of measures can be used to assess the effect of instruction on learning, performance, retention, and transfer of skills from instruction to operations. The effect size (Coe, 2002) of tutoring strategies in many instances is the critical measure of the value or impact of the instruction provided. ITSs are often compared to the effectiveness of traditional classroom training. Several investigations into the effect size of ITSs in the last few years demonstrate their significant advantage over classroom training (Kulik & Fletcher, 2015; Ma, Adesope, Nesbit, & Liu, 2014; Pane, Griffin, McCaffrey, & Karam, 2014; Steenbergen-Hu & Cooper, 2013, 2014; VanLehn, 2011), but their development cost remains high and the complexity of the domains they support today is limited, but continuing to grow beyond mathematics and physics to pathology (El Saadawi et al., 2008), military tactics (Boyce, Cruz, & Sottilare, 2017), medical casualty care (Ocumpaugh et al., 2017; Sottilare, Hackett, Pike, & LaViola, 2016), and psychomotor domains (Kim, Dancy, Goldberg, & Sottilare, 2017).

Tutor—User Interface

Human tutors provide information, feedback, support, and guidance to the learner through both verbal and non-verbal communications. ITSs attempt to replicate this function through the tutor—user interface (TUI) which can take many forms. Fig. 1 shows many interactions possible between an ITS and a learner:

- Natural Language Feedback Window – provides a virtual human to engage in a dialogue with the learner (closest communication mode to human tutoring).
- Conversation Log – provides a rolling text account of the communications between the tutor and the learner; can be used by the learner to review guidance or by experimenters to understand behaviors leading to better learning.

Fig. 1. Generic Tutor—User Interface.

- Tutor Text Feedback Window – provides textual feedback from the tutor; usually used in lieu of a natural language interface or to supplement natural language dialogue to promote clarity.
- Content Presentation Window – provides content (interactive media) relevant to the domain under instruction; can vary from simple text to interactive 3-D immersive simulations as levels of interactive multimedia instruction (Schwier & Misanchuk, 1993).
- Learner Response Window – provides a space for the learner to type in responses (ala chat).

In designing a tutor for teams, each team member will require a TUI as shown in Fig. 1, but communication scheme for the tutor will be more complex. In an individual ITS, all of the communication is between the learner and the tutor. In scaling ITSs to support team learning, the communication is not simply broadcasted, but multi-casted where there is communication between the tutor and each learner, the tutor and all of the learners, the tutor and subsets of the learners, and between pairs and groups of learners. Especially important is the communication between learners on a team since these interactions indicate behavioral, attitudinal, and cognitive markers for team states (Sottilare, Burke, et al., 2017) and shared mental models (Fletcher & Sottilare, 2017).

TEAM TUTORING CHALLENGES AND APPROACHES

As noted previously, ITSs have demonstrated superior effect over traditional classroom instruction and are now considered on par with expert human tutors for individual task domains. A natural next step is to apply machine-based tutoring to small teams. The payoff for successful application of ITSs to team domains is high given this proven effectiveness and the large scale focus of teams in both military and civilian instructional domains. However, there are significant barriers to overcome to realize effective and efficient ITSs for team instructional domains (Sottilare, 2018). If we examine the tutoring process for individual task domains demonstrated in the *learning effect model* (LEM; Sottilare, 2012; Sottilare, Burke, et al., 2017), the key steps include: (1) acquisition of learner data, (2) assessment of learner states, (3) selection of strategies and tactics, (4) application of strategies and tactics, and (5) assessment of effect. While the LEM for teams is more complex, the process itself is not that different. The key steps in the team LEM process include: (1) acquisition of individual learner and team interaction data, (2) assessment of individual learner and team states, (3) selection of strategies and tactics, (4) application of strategies and tactics, and (5) assessment of effect. Let's discuss the challenges associated with each key step in the team LEM process.

Acquisition of Individual Learner and Team Interaction Data

The ability of an ITS to acquire data from both individual members of the team and interactions between them is critical to determining individual learner and team states. The individual learner data includes behavioral and physiological data which can be used to ascertain various learner states (e.g., performance, emotional states, motivation). The interaction between team members is primarily their communications and forms the basis of team data which can be used to ascertain team states (e.g., team learning and performance). This team data which includes behavioral markers, team attitudes, and shared cognition as described by Sottilare, Burke, et al. (2017) must be reliably acquired so it can be processed by machine learning algorithms and other techniques into team states. Data acquisition can vary depending upon the task domain and the instructional delivery mechanism (e.g., local, distributed, shared virtual environment). The data acquisition method should be unobtrusive so as not to interfere with team interaction and the team learning process, but should also provide the trigger for identifying learner and team states leading to action by the tutor. Approaches for team and collaborative learning environments vary, but the nature of verbal communications between team members has made real-time speech processing a tool of choice for acquiring and assessing natural language. This may be especially true for newly formed teams or teams made up of novices in the domain of instruction.

One approach to acquiring and processing natural language is deep learning, "a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks" (ANNs; Brownlee, 2016). Deng and Yu (2014) note that with sufficient computational power, machine can now recognize objects and translate speech in real-time, but error rates over 20% for individual speakers may not translate to successful recognition of speech acts in team environments where team members speak over one another or are masked by ambient noise in the training environment. Speech acts are utterances which infer action, particularly with regard to their intention, purpose, or effect.

Assessment of Individual Learner and Team States

Once the tutor has an accurate assessment of what was said by one team member and intended for one or more other team members, the next step in the LEM process is to assess the context of its impact on teamwork and thereby learning and performance. The primary challenge in accurately classifying both individual learner and team states are the large number of conditions represented in individual learner models, team models, and training environments which drive decisions by adaptive tutors. A key is understanding which behavioral, attitudinal, and cognitive markers are associated with which teamwork states.

Sottilare, Burke, et al. (2017) noted several communication markers that identify teamwork states that are antecedents to successful learning and performance. According to Salas, Rosen, Burke, and Goodwin (2009), teamwork states include cooperation (motivational drivers), coordination (behaviors), cognition (common understanding), coaching (leadership activities), conflict resolution (procedures), and conditions (norms and support). As noted earlier, problems with the availability and stability of data can increase uncertainty and degrade the accuracy of machine learning classification processes. So, even though the tutor acquires sufficient data in the form of teamwork markers to make an accurate classification of teamwork states, the corruption of this data in any fashion will likely result in poor classification accuracy. One approach to overcoming uncertainty in the classification process is to improve the clarity of what is said, who said it, who it is directed toward, and the associated intent of the message. The answer to improving the quality of communications may be to increase the numbers of sensors, configure them to optimize acquisition, or apply/develop better sensors. While the quality of verbal communications is a major factor in teamwork and team viability (Pitts, Wright, & Harkabus, 2012), other verbal factors (e.g., pitch and amplitude) and non-verbal factors (e.g., proximity) may also provide other mechanisms needed to understand the relationship between team members.

One approach to understanding teamwork may be through the identification of team member emotions through their verbal communications. People often infer emotions from vocal characteristics (Planalp, 1998). "The assessment of vocal characteristics appears to be especially useful in understanding levels of emotional arousal, with higher levels of pitch and amplitude associated with higher levels of arousal" (Mauss & Robinson, 2009, p. 225). However, increased arousal may be associated with both positive and negative valence (Mehrabian, 1996) which complicates the classification of positive or negative teamwork states.

Proximity of team members may be another approach to understanding team communications. Hoegl and Proserpio (2004) found that team members' proximity is significantly related to teamwork quality and the magnitude of the relationship between proximity and teamwork quality varied among the six teamwork quality factors with communication, coordination, mutual support, effort, and cohesion being positively related to the proximity of team members and the balance of team member contributions showing no significant relationship. Martinez-Maldonado et al. (2017) studied the feasibility and potential of proximity analytics for teaching and learning in a team-based simulation environment and found that multimodal sensors coupled with data mining techniques can provide educational researchers and trainers with the computational tools needed to examine team activities.

Selection and Application of Strategies and Tactics for Effect

The next step in the LEM process is the selection of strategies (plans for action by the tutor) and tactics (actions by the tutor). Strategies may take the form of generalized (domain-independent) policy design to fulfill a learning or performance goal. In GIFT, strategies are generic categories of possible next actions to be taken by the tutor and include, but are not limited to: ask the learner a question, provide the learner a hint, pump the learner for information, direct the learner, support the learner, or prompt the learner to take action. The specific tactics or actions taken by the tutor next are dependent upon the context of the learning environment (e.g., where the learner is in the course material or scenario).

For example, an individual learner may be asked a question by the tutor, but the selection of that question is based on the domain concept or learning objective that the student is currently working on. In the GIFT, the question is selected from a question bank based on metadata that associates the selected question with a specific concept and/or learner attribute (e.g., low motivation). For team tutoring, the strategies might be based on the state(s) of the team and the tactics based on the team's progress toward comprehension and competence with a specific concept or set of concepts. Whether the tutoring is for an individual or a team, the selection of strategies and tactics should be based on a high probability that once applied, the strategy or tactic will enhance learning and/or performance.

The challenge is to find a method or methods that will optimally select available strategies and tactics and allow the tutor to improve the effect of its selections over time much the same as in reinforcement learning processes (Mitchell, 1997). For example, an agent-based approach might employ the autonomous agents that observe both the learner and the instructional environment (e.g., simulation or problem set). Each time the tutoring agent takes an action in some state (e.g., a set of learner and environmental conditions), the agent receives a reward commensurate with the current or projected future value of the action. Value can be estimated in terms of learning outcomes and for a cognitive task might include measures of cognition related to the learner's progression through stages of a revision of Bloom's Taxonomy (Krathwohl, 2002): recall, understanding, applying, analyzing, evaluating and creating, or some other valuation criteria. For teams, Soller (2001) advocates collaborative learning skills in terms of conversational skills and action by members of the team. The ability of the tutor to recognize actions associated with skill development could be used as a measure of learning effect. Actions by the tutor that encouraged, directed, or reinforced appropriate learner communications could lead to the development of active learning skills (request, inform, motivate), conversational skills (task, maintain, acknowledge), and/or creative conflict skills (argue, mediate). Sentence openers in Soller's taxonomy (2001) could be used as behavioral markers to indicate communication skill development.

Now that we have explored some of the processes and challenges in team tutoring, a next step is to discuss those processes in terms of the structure and use of this book.

HOW TO USE THIS BOOK

In order to help refine your understanding of ITS processes and how they might be applied to team training and educational domains, the book is organized into four sections. Section 1 includes chapters that provide an understanding of concepts related to team training (adaptive and non-adaptive instruction) along with approaches that contrast team taskwork (domain-dependent) and teamwork (domain-independent). Section 2 focuses on team assessment and feedback mechanisms for teams. Significant effort is focused on understanding the differences in complexity between assessment and feedback for individuals vs teams. Next, Section 3 addresses current and emerging adaptive team training applications, their effect and their weaknesses. Discussion in this section also focuses on how adaptive instructional tools like ITSs might be used to make non-adaptive team training more adaptive and responsive to the learning needs of teams. Finally, in Section 4 we explore multidisciplinary perspectives on team tutoring. It takes a village to build a tutor and in this section we discuss the roles of authors, instructional designers, human factors scientists, software programmers, and subject matter experts in the context of their contributions to authoring and evaluating adaptive instruction. In this way, we strive to provide a flexible means for the reader to expand their knowledge of ITS design and application while simultaneously offering a variety of perspectives on the problem of authoring and evaluating ITSs.

REFERENCES

Aleven, V., McLaren, B., Sewall, J., & Koedinger, K. (2006). The cognitive tutor authoring tools (CTAT): Preliminary evaluation of efficiency gains. In *Intelligent Tutoring Systems* (pp. 61–70). Berlin: Springer.

Boyce, M., Cruz, D., & Sottilare, R. (2017). Interpretative phenomenological analysis for military tactics instruction. Advances in human factors, business management, training and education, advances in intelligent systems and computing (p. 498). Cham, Switzerland: Springer International Publishing. Retrieved from https://doi.org/10.1007/978-3-319–42070-7_58.

Brownlee, J. (2016). *What is deep learning? Machine learning mastery*. Retrieved from https://machinelearningmastery.com/what-is-deep-learning/. Accessed on August 21, 2017.

Burke, S., Sottilare, R., Johnston, J., Sinatra, A., & Salas, E. (2017). *Towards a scientifically rooted design architecture of team process and performance modeling in adaptive, team-based intelligent tutoring systems*. Orlando, FL: US Army Research Laboratory.

BusinessDictionary.com. (2017). *Performance defined.* Retrieved from http://www.businessdictionary.com/definition/performance.html. Accessed on August 28, 2017.

Coe, R. (2002). It's the effect size, stupid: What effect size is and why it is important. Paper presented at the Annual Conference of the British Educational Research Association, University of Exeter, UK.

Deng, L., & Yu, D. (2014). Deep learning: Methods and applications. *Foundations and Trends® in Signal Processing*, *7*(3–4), 197–387.

El Saadawi, G. M., Tseytlin, E., Legowski, E., Jukic, D., Castine, M., Fine, J., … Crowley, R. S. (2008). A natural language intelligent tutoring system for training pathologists: Implementation and evaluation. *Advances in Health Sciences Education*, *13*(5), 709–722.

Fletcher, J. D., & Sottilare, R. A. (2017). Shared mental models in support of adaptive instruction for team tasks using the GIFT tutoring architecture. *International Journal of Artificial Intelligence in Education*, *28*, 265–285. doi:10.1007/s40593-017-0147-y

Graesser, A. C. (2016). Conversations with AutoTutor help students learn. *International Journal of Artificial Intelligence in Education*, *26*(1), 124–132.

Hackman, J. R., & Wageman, R. (2005). A theory of team coaching. *Academy of Management Review*, *30*(2), 269–287.

Hoegl, M., & Proserpio, L. (2004). Team member proximity and teamwork in innovative projects. *Research Policy*, *33*(8), 1153–1165.

Kim, J. W., Dancy, C., Goldberg, B., & Sottilare, R. (2017, July). A cognitive modeling approach-does tactical breathing in a psychomotor task influence skill development during adaptive instruction? In *International conference on augmented cognition* (pp. 162–174). Cham, Switzerland: Springer.

Krathwohl, D. R. (2002). A revision of Bloom's taxonomy: An overview. *Theory into Practice*, *41*(4), 212–218.

Kulik, J. A., & Fletcher, J. D. (2015). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research*, *86*(1), 42–78. doi:10.3102/0034654315581420

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology*, *106*(4), 901–918. doi:10.1037/a0037123

Martinez-Maldonado, R., Yacef, K., dos Santos, A. D. P., Shum, S. B., Echeverria, V., Santos, O. C., … Pechenizkiy, M. (2017, July). Towards proximity tracking and sensemaking for supporting teamwork and learning. In 2017 IEEE 17th international conference on advanced learning technologies (ICALT) (pp. 89–91). IEEE.

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition and emotion*, *23*(2), 209–237.

Mehrabian, A. (1996). Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. *Current Psychology*, *14*(4), 261–292.

Mitchell, T. M. (1997). *Machine learning*. Boston, MA: McGraw-Hill. ISBN: 978-0-07–042807-2.

Ocumpaugh, J., Andres, J. M., Baker, R., DeFalco, J., Paquette, L., Rowe, J., … Sottilare, R. (2017). Affect dynamics in military trainees using vMedic: From engaged concentration to boredom to confusion. In *Proceedings of the artificial intelligence in education conference*, Wuhan, China, June 2017.

Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014). Effectiveness of cognitive tutor algebra I at scale. *Educational Evaluation and Policy Analysis*, *36*(2), 127–144. doi:10.3102/0162373713507480

Pitts, V. E., Wright, N. A., & Harkabus, L. C. (2012). Communication in virtual teams: The role of emotional intelligence. *Journal of Organizational Psychology*, *12*(3–4), 21.

Planalp, S. (1998). Communicating emotion in everyday life: Cues, channels, and processes. In P. A. Andersen, K. Laura, & L. K. Guerrero (Eds.). *Handbook of communication and emotion: Research, theory, applications, and contexts* (pp. 29–48). San Diego, CA: Academic Press.

Psotka, J., Massey, L. D., & Mutter, S. A. (Eds.). (1988). *Intelligent tutoring systems: Lessons learned*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Salas, E. (2015). *Team training essentials: A research-based guide*. London: Routledge.

Salas, E., Rosen, M. A., Burke, C. S., & Goodwin, G. F. (2009). The wisdom of collectives in organizations: An update of the teamwork competencies. *Team effectiveness in complex organizations: Cross-disciplinary perspectives and approaches* (pp. 39–79). New York, NY: Routledge.

Schwier, R., & Misanchuk, E. R. (1993). *Interactive multimedia instruction*. Englewood Cliffs, NJ: Educational Technology.

Soller, A. (2001). Supporting social interaction in an intelligent collaborative learning system. *International Journal of Artificial Intelligence in Education (IJAIED)*, *12*, 40–62.

Sottilare, R. (2012). Considerations in the development of an ontology for a generalized intelligent framework for tutoring. *International defense & homeland security simulation workshop in proceedings of the I3M conference*. Vienna, Austria, September 2012.

Sottilare, R. (2016). Lecture notes from the intelligent tutoring system design course (IDS 6938). University of Central Florida Modeling & Simulation Program. Fall 2016.

Sottilare, R. (2018). A comprehensive review of design goals and emerging solutions for adaptive instructional systems. *Technology, Instruction, Cognition, & Learning (TICL) Journal*, *11*, 5–38.

Sottilare, R., Brawner, K., Sinatra, A., & Johnston, J. (2017). *An updated concept for a generalized intelligent framework for tutoring (GIFT)*. Orlando, FL: US Army Research Laboratory. May 2017. doi:10.13140/RG.2.2.12941.54244

Sottilare, R. A., Burke, C. S., Salas, E., Sinatra, A. M., Johnston, J. H., & Gilbert, S. B. (2017). Towards a design process for adaptive instruction of teams: A meta-analysis. *International Journal of Artificial Intelligence in Education*, *28*, 225–264. doi:10.1007/s40593-017-0146-z

Sottilare, R., Graesser, A., Hu, X., & Goodwin, G. (2017). Introduction to assessment methods and GIFT. In *Design recommendations for intelligent tutoring systems: Volume 5 – Assessment methods*. Army Research Laboratory, Orlando, Florida. ISBN: 978-0-9977257-2-8.

Sottilare, R., Hackett, M., Pike, W., & LaViola, J. (2016). Adaptive instruction for medical training in the psychomotor domain. *The Journal of Defense Modeling and Simulation*, *14*, 331–343. doi:10.1177/1548512916668680

Steenbergen-Hu, S., & Cooper, H. (2013). A meta-analysis of the effectiveness of intelligent tutoring systems on K–12 students' mathematical learning. *Journal of Educational Psychology*, *105*(4), 970–987. doi:10.1037/a0032447

Steenbergen-Hu, S., & Cooper, H. (2014). A meta-analysis of the effectiveness of intelligent tutoring systems on college students' academic learning. *Journal of Educational Psychology*, *106*(2), 331–347. doi:10.1037/a0034752

Van Berio, M. P. (1997). Team training vs. team building and cooperative learning: Defining the field of research (team training vs team building en cooperatief leren: Afbakening van het onderzoeksterrein) (No. TNO-TM-97-B019). Human Factors Research Inst Tno Soesterberg (Netherlands).

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, *46*(4), 197–221.