GIFT as a Framework for

Self-Improvable Digital Resources in SIAIS

**Xiangen Hu1,2, Zhiqiang Cai1, Arthur C. Graesser1, and Jody L. Cockroft1**

The University of Memphis1, Central China Normal University2

# Introduction

There are four components in a minimalist model of Self-Improvable Adaptive Systems (SIAIS) [(Hu, Tong, Cai, Cockroft, & Kim, 2019)](https://paperpile.com/c/54huDR/K3h0). These four components are 1) human learners that are assumed constantly self-improving (i.e., learning); 2) self-improvable learning resources that are either human resources (trainers/teachers, for example) or digital resources such as digital tutors which are capable of changing (improving) constantly; 3) learning environments that are diverse physical or virtual locations, contexts, and cultures in which students learn; 4) learning processes that are instructional sequence for any given domain for particular learner groups (such as grades). One publicly available important framework for self-improvable digital resource in SIAIS is Generalized Intelligent Framework for Tutoring (GIFT), which is an empirically-based, service-oriented framework of tools, methods and standards to make it easier to author computer-based tutoring systems (CBTS), manage instruction and assess the effect of CBTS, components and methodologies [(“Overview - GIFT - GIFT Portal,” n.d.)](https://paperpile.com/c/54huDR/uMfZS). In this paper, we take AutoTutor as an example of self-improvable tutoring systems and discuss the rule GIFT may play as a framework of self-improvable learning resources.

# Self-improvable learning resources

Based on Hu et al (in press), *self-improvable learning resources* are defined as those learning resources that can update, retrieve, and utilize their associated memory of the learning activities. The human learner is obviously self-improvable and is constantly working to self-improve. Human teachers/trainers, and human study mates are also self-improvable and constantly improving as the result of constant interacting with human learners. Unfortunately, not all digital learning resources are self-improving. Relevant to the focus of the current paper, we are interested in specially designed digital resources that are self-improvable. As an example, AutoTutor is one such specially designed digital resources.

## AutoTutor

AutoTutor [(Graesser, Wiemer-Hastings, Wiemer-Hastings, & Kreuz, 1999; Nye, Graesser, & Hu, 2014)](https://paperpile.com/c/54huDR/bQfxc+i5lA) is an intelligent tutoring system that holds conversations with the human learner in natural language. AutoTutor has produced learning gains across multiple domains (e.g., computer literacy, physics, critical thinking). Three main research areas are central to AutoTutor: human-inspired tutoring strategies, pedagogical agents, and technology that supports natural language tutoring [(“AutoTutor,” n.d.)](https://paperpile.com/c/54huDR/oSHY). For the purpose of the current paper, we list a few less known properties of AutoTutor that make it a self-improvable digital resource in SIAIS. These properties make AutoTutor a variable controlled system. To illustrate, we list a few variable controllable components of AutoTutor that can influence the behavior of AutoTutor:

*Answer Grading Model*. AutoTutor conversation is often referred to as Expectation-Misconception Tailored (EMT) conversation, in which a human learner learns by constructing an acceptable answer to a main question through answering a sequence of hint/prompt questions asked by AutoTutor. An AutoTutor main question usually requires an answer of 3 to 10 sentences. A hint/prompt question targets one aspect of the answer. The answer to a hint question is usually a sentence or a clause, while an answer to a prompt is usually a word or phrase. AutoTutor intelligently selects hint/prompt questions based on the learner’s input, which could be a good answer, a partial answer, a misconception, an irrelevant answer or even not an answer (e.g., a question). The AutoTutor answer grading model is responsible for classifying the learner’s inputs. The model is trained through deep learning neural network (Cheng, Cai & Graesser, 2018) with semantic features. For each newly developed AutoTutor application, AutoTutor uses a pre-trained model for early answer grading. When enough learning data is collected, the domain specific model is trained. The model could be further improved when more data is collected. Thus, the answer grading model is considered as an important variable that can be changed over time to improve AutoTutor’s performance.

*Avatars*: AutoTutor employs several conversational avatars when interact with students. The avatars can play different roles such as computer tutors or computer students. Each of the avatars can have an assigned “personality” serving different functions during tutoring. For example, a tutor avator could have warm, neutral or cold personality; a peer student avatar may have the personality as a student leader, a hard working learner, an aggressive competitor, etc. The “personality” of an avatar is reflected by its facial emotions and its commonly used speeches, called “canned expressions”. The avatar face can be selected from available avatar library. The canned expressions can be revised over time. Thus, avatars are a variable in AutoTutor.

*Scripts:* AutoTutor uses author prepared scripts for avatars. However, when learning data is collected, the scripts could be changed over time. For example, useless speeches could be removed; inadequate questions and speeches could be revised; and missing questions and speeches could be added. Moreover, typical utterances from human learners could be added as speeches for avatars that play the role of peer students.

*Rules*: AutoTutor uses a set of “if-then” rules to determine what to do next in any given state. A state is determined by the learning history (what has happened so far) and the current input, including natural language input and “world events”, such as an interaction between the learner and an interactive element on the application interface, a time controlled change in the learning environment, etc. A rule set is often embedded with pedagogical strategies. For example, a vicarious learning rule set supports conversation between a tutor avatar and a peer student avatar, with minimal involvement of the human learner. A tutoring rule set specifies the way how to interact with learners who have medium level knowledge about the topic under discussion. A teachable agent rule set provides learners the opportunity to learn through teaching a peer student avatar. Each rule in a rule set can be changed over time. The criteria used to select a rule set is also changeable. Thus AutoTutor conversation rules are also a variable.

## GIFT as a framework for Self-Improvable digital resources in SIAIS

There are many learning resources like AutoTutor that can be integrated into GIFT. GIFT framework requires any ITS based on GIFT (GIFTITS) is an integration of four core modules [(“Overview - GIFT - GIFT Portal,” n.d.)](https://paperpile.com/c/54huDR/uMfZS): **Sensor Module, Learner Module**, **Pedagogical Module**, and the **Domain Module**. The current prototype of GIFT (<https://cloud.gifttutoring.org/>) is a GIFTITS. The Sensor Module has interfaces to support commercial sensors (e.g., Affectiva Q-Sensor) and its function is to format, process and store sensor data. The Domain Module provides domain content to support training, assesses trainee performance against standards, and provides domain-specific feedback to the trainee when the Pedagogical Module identifies the need for feedback based on trainee performance. The Trainee Module uses trainee performance, historical data (e.g., past performance) and sensor data to determine the trainee’s cognitive and affective state. Current implementation of GIFT is primarily for content authoring and resource integration. Each of these Modules is interchangeable through the virtue of interfacing standards. This allows each Module designer to select the type of approach that they believe is suited towards instruction. For instance, a sample configuration may have a webcam sensor that interprets Facial Action Units (FACs), a rule-based performance assessment, a Feedback Generation Engine that generates varying levels of hints upon request, a finite state machine of trainee assessment, and pedagogy that gives hints on failed problems.

Relevant to the focus of the current paper, one very important implementational properties of the current GIFT prototype is its modularity. All modules of GIFTITS are variable controlled. A each module is controlled by an XML file. For example, a domain knowledge file (DKF) contains the information needed to execute on a single lesson. Learner Configuration File is an XML that configures the learner module to support building learner states from inputs such as sensor data and performance assessments. There are configuration files for sensor module (SensorConfigurationFile), pedagogy module (PedagogicalConfigurationFile) that are controls behavior of GIFTITS when interact with learner. In addition, other variables are also separately specified (in common.properties file). This implementation properties of the GIFT prototype shows that GIFTITS can be variable controlled hence self-improvable.

# Self-improvability of learning resources

It was pointed out earlier that *self-improvable* learning resources are defined as those learning resources that can update, retrieve, and utilize their associated memory of the learning activities [(Hu et al., 2019)](https://paperpile.com/c/54huDR/K3h0). Having variable controlled components will only make a digital resources *self-improvable* but not necessarily self-improving. Other key properties are needed. In the case of AutoTutor, its self-improvability is due to three key factors: a) AutoTutor is an cloud-based implementation with constant connection with a Learner Record Store (LRS) [(Nye et al., 2014)](https://paperpile.com/c/54huDR/bQfxc). b) Behaviors of AutoTutor are variable controlled. c) The variables that control AutoTutor’s behaviors could be changed based on the behavioral data collected in LRS. The same is for GIFT. Current implementation of AutoTutor only has a). The self-improvability of AutoTutor depending on b) and c). Only proper implementation of b) and c) can make AutoTutor self-improving.

## Self-improvability of GIFTITS

We have argued that ITS implementation based on GIFT (as shown in the current GIFT prototype implementation) may have all modules and components variable controlled hence self-improvable. To make GIFTITS truly self-improving, additional key properties need to be added:

1. System behavior of GIFTITS and human learner interaction behavior should be captured and stored within the same data scheme (such as xAPI). Current used of the behavioral data are collected mostly for post-hoc analysis. When the data is used to make GIFTITS self-improvable, there are special requirements, For example, the speed of retrieving and processing data should be fast enough for real-time feed back to the GIFTITS. Because the data will be used to improve GIFTITS, additional requirement for the data schema need to be considered (Hu et al impress).
2. A collection of APIs need to be created that connect all variables of GIFTITS to the data store. These APIs will need to be constantly computing values based system behavior data and capable of real-time updating GIFTITS. The output of these APIs can either be an updated XML file (such as the DKF, PedagogicalConfigurationFile, or parameter values in the common.properties file).

With 1) and 2) can only make GIFTITS self-changable. There is no mechanism to guarantee the GIFTITS is actually improving the learning experience and effectiveness. So it is very important to ensure self-improvability is achieved. In order to make this happen, a set of theory-driven empirically verified ideal tutoring behaviors need to be specified parametrically. For example, based on Graesser et al. [(2008)](https://paperpile.com/c/54huDR/p5tWb/?noauthor=1) GIFTITS needs to ask deep questions to during tutoring session, so for effective ITS, there might be a minimum requirement for number of deep questions asked during a given period of time. In addition an effective ITS in a given domain may have an optimal combinations of questions at different levels [( Graesser & Person, 1994)](https://paperpile.com/c/54huDR/Bzkj). So in addition to 1) and 2) listed above, self-improvability of GIFTITS needs to have

1. A pre-set of ideal (effective and efficient) tutoring strategies specified computationally so it can be used to guide APIs of 2).

# Recommendation and Future Research

Any GIFTITS can be self-improvable learning resource due to its design with variable controlled modules and components. Self-improving GIFTITS is possible if the self-improbability requirements (1-3) are met. Consider building self-improving GIFTITS as ultimate goal, it is necessary to enhance GIFT framework with the three self-improbability requirements. Specifically,

1. A extended behavior xAPI-like data profile (Hu et al. in press) need to be created that is capable of capture all interactions between GIFTITS and human learner such that all system behavior of GIFTITS are captured similar to that of human learner’s behavior.
2. A collection of optimum domain-specific task-dependent tutoring strategies need to be created. These optimum tutoring strategies are computationally specifiable. For example, if a conversation-based GIFTITS is created based on Expectation-misconception tailored (EMT) dialog [(Olney, Graesser, & Person, 2010)](https://paperpile.com/c/54huDR/JKEB), there exists an optimum combination of hints, prompts, pumps, and elaborations [(Graesser et al., 1999; Olney et al., 2010)](https://paperpile.com/c/54huDR/i5lA+JKEB).
3. A set of APIs needed to be created. These APIs that are constantly monitoring GIFTITS behaviors and make real-time changes of variable values in GIFTITS modules and components of based on 2).

**References**

[AutoTutor. (n.d.). Retrieved April 13, 2019, from](http://paperpile.com/b/54huDR/oSHY) <http://ace.autotutor.org/IISAutotutor/index.html>

[Graesser, A. C., Halpern, D. F., & Hakel, M. (2008). 25 principles of learning. Task Force on Lifelong Learning at Work and at Home Washington, DC.](http://paperpile.com/b/54huDR/p5tWb)

[Graesser, A. C., & Person, N. K. (1994). Question Asking during Tutoring. *American Educational Research Journal*, *31*(1), 104.](http://paperpile.com/b/54huDR/Bzkj)

[Graesser, A. C., Wiemer-Hastings, K., Wiemer-Hastings, P., & Kreuz, R. (1999). AutoTutor: A simulation of a human tutor. *Cognitive Systems Research*, *1*(1), 35–51.](http://paperpile.com/b/54huDR/i5lA)

[Hu, X., Tong, R., Cai, Z., Cockroft, J. L., & Kim, J. W. (2019). Self-Improvable Adaptive Instructional Systems (SIAIS) -- A proposed model. In A.M. Sinatra, A. Graesser, X. Hu, V. Rus, A. Olney (Ed.), *Design Recommendations for Intelligent Tutoring Systems: Volume 7 -- Self-Improving Systems*. Orlando, FL: U.S. Army Research Laboratory.](http://paperpile.com/b/54huDR/K3h0)

[Nye, B. D., Graesser, A. C., & Hu, X. (2014). AutoTutor and Family: A Review of 17 Years of Natural Language Tutoring. *International Journal of Artificial Intelligence in Education*, *24*(4), 427–469.](http://paperpile.com/b/54huDR/bQfxc)

[Olney, A. M., Graesser, A. C., & Person, N. K. (2010). Tutorial Dialog in Natural Language. In R. Nkambou, J. Bourdeau, & R. Mizoguchi (Eds.), *Advances in Intelligent Tutoring Systems* (pp. 181–206). Berlin, Heidelberg: Springer Berlin Heidelberg.](http://paperpile.com/b/54huDR/JKEB)

[Overview - GIFT - GIFT Portal. (n.d.). Retrieved February 21, 2019, from](http://paperpile.com/b/54huDR/uMfZS) <https://gifttutoring.org/projects/gift/wiki/Overview>

# ABOUT THE AUTHORS

***Dr. Xiangen Hu*** *is a professor in the Department of Psychology, Department of Electrical and Computer Engineering and Computer Science Department at The University of Memphis (UofM) and senior researcher at the Institute for Intelligent Systems (IIS) at the UofM and is professor and Dean of the School of Psychology at Central China Normal University (CCNU). Dr. Hu received his MS in applied mathematics from Huazhong University of Science and Technology, MA in social sciences and Ph.D. in Cognitive Sciences from the University of California, Irvine. Dr. Hu is the Director of Advanced Distributed Learning (ADL) Partnership Laboratory at the UofM, and is a senior researcher in the Chinese Ministry of Education’s Key Laboratory of Adolescent Cyberpsychology and Behavior.*

***Zhiqiang Cai*** *is a Research Assistant Professor with the Institute for Intelligent Systems at the University of Memphis. He has a M.S. degree in mathematics received in 1985 from Huazhong University of Science and Technology, P. R. China. After 15 years of teaching mathematics in colleges, he has worked in the field of natural language processing and intelligent systems. He is the chief software designer and developer of Coh-Metrix, OperationAries, CSAL AutoTutor and many other text analysis tools and conversational tutoring systems. He has co-authored over 70 publications****.***

***Arthur C. Graesser*** *is a professor in the Department of Psychology and the Institute of Intelligent Systems at the University of Memphis and is a Senior Research Fellow in the Department of Education at the University of Oxford. He received his Ph.D. in psychology from the University of California at San Diego. Dr. Graesser’s primary research interests are in cognitive science, discourse processing, and the learning sciences. More specific interests include knowledge representation, question asking and answering, tutoring, text comprehension, inference generation, conversation, reading, education, memory, emotions, computational linguistics, artificial intelligence, human-computer interaction, and learning technologies with animated conversational agents. He has published over 500 articles in journals, books, and conference proceedings.*

***Jody L. Cockroft.****is a Research Specialist at the University of Memphis in the Institute for Intelligent Systems. Prior to joining the University of Memphis, she was with the University of Tennessee Health Science Center in Memphis where she was involved in with various clinical trials and bench research for over twenty years. She earned her A.A. from the University of Tampa and her B.S. from the University of Memphis. She has been working with the UofM team for the past five years on the Army Research Laboratory project on the Generalized Intelligent Framework for Tutoring (GIFT) and the Advanced Distributed Learning (ADL) Academy projects and the Advanced Learning Theories, Technologies, Applications and Impacts (ALTTAI) Consortium efforts. She is serving as the Treasurer for the IEEE Project 2247 Adaptive Instructional Standards working Group.*