

ElectronixTutor: An Adaptive Learning Platform with Multiple Resources

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ABSTRACT

The development of a complex, adaptive learning platform presents many challenges, particularly in difficult topics like electrical engineering that require deep understanding of technical concepts and their interrelationships. One approach to handling this challenge is to build a system that integrates an ensemble of adaptive intelligent learning environments as well as static learning resources (technical manuals, diagrams, simulations) so that the right resource is delivered to the right person at the right time. We instantiated this approach in a project funded by the Office of Naval Research with technology and learning standards guided by the Army Research Laboratory and Advanced Distributed Learning Initiative. The ElectronixTutor system was developed in an open-source learning platform on the web, instantiated on Moodle, with several intelligent tutoring systems (AutoTutor, Dragoon, LearnForm, ASSISTments, and BEETLE-II) that have demonstrated significant learning gains across various domains and depths of instruction. This paper focuses on three primary achievements, situated within the general development of the system as a whole. First, we describe the creation of a quantitative interlingua (learning standard) that is based on knowledge components in order to translate progress across learning resources into a comprehensive learner model. Second, we specify the procedures by which our recommender system evaluates and suggests items appropriate to the topic, depth, modality, and knowledge components for individual learners. We also describe other components of the system, including the user interface, in-person course integration, instruction calendars, and the learning record store. Third, we report an initial study that collects data from college students who learn about electronic circuits with the system. While the full results of this study are not yet final, the methodology and implementation into classroom settings demonstrates capacity for relatively easy adoption and expansion of classroom capabilities by offering coordination of multiple types of intelligent tutoring practice capabilities in a comprehensive learning experience.

ABOUT THE AUTHORS

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PREFACE

The integration of diverse learning resources into a unified platform affords tailored instruction to individual learners at a level vastly more personalized than classroom learning, more scalable than one-on-one tutoring, and more economical than either. Such a platform allows access to both conventional resources (e.g., reference texts) and intelligent tutoring systems (ITSs) that model and adaptively respond to the learner's particular knowledge, skills, and abilities. Developing a platform to leverage these benefits presents novel challenges, including (1) how to develop a unified learner model as they progress across different learning resources and (2) how to use the learner model to recommend relevant learning resources with the appropriate difficulty, depth, media, interactivity, and other characteristics to optimize learning and engagement. This paper describes the development and initial testing of ElectronixTutor, a system that includes several independently validated ITSs alongside widely used static text materials to teach fundamental and intermediate electronics.

INTRODUCTION

Intelligent Tutoring Systems

ITSs are computer learning environments designed to help students master knowledge and skills by implementing intelligent adaptive algorithms and procedures that exhibit fine-grained adaptivity to the students' progress (Graesser, Rus, & Hu, 2017; Woolf, 2009). No two learners are identical. They have varying levels of mastery, particular areas of difficulty or omission, and unique characteristics that impact learning. This variability precludes a singular approach and progression to teaching complex topics. ITSs extend beyond conventional computer-based training with intelligent mechanisms at a fine-grained level of knowledge acquisition and adaptivity. Although more complex computer-based training may include coarse adaptivity, these do not extend past an if-then decision tree that includes limited variability based on their performance and typically a relatively fixed progression of content. ITSs track learner characteristics at a finer grain size and track a variety of knowledge, skills, abilities, and other psychological traits (e.g., grit). This adaptivity of ITSs draws from advances in both artificial intelligence and cognitive science research (Sottolare et al., 2014; VanLehn, 2006; Woolf, 2009). Adaptivity in an ITS is typically sensitive enough to learner characteristics that the sequence of progression through recommended content will be unique to each learner.

The utility of ITSs has been demonstrated in an extensive array of domains, including STEM (science, technology, engineering, & mathematics) education. Efforts in well-defined areas of mathematics such as algebra and geometry include *Cognitive Tutors* (Aleven et al., 2009; Koedinger et al., 1997; Ritter et al., 2007) and *ALEKS* (Falmagne et al., 2013). The technology field has inspired the development of ITSs for electronics (*SHERLOCK*, Lesgold et al., 1992; *BEETLE-II*, Dzikovska et al., 2014) and digital information technology (*Digital Tutor*, Fletcher & Morrison, 2012).

Complementing these mathematically and analytically oriented approaches, some ITSs focus on deep reasoning by means of verbal interaction (Johnson & Lester, 2016). These hold conversations in natural language, encouraging learners to explain complex concepts in their own words to encourage and ensure depth of understanding. To accomplish this, conversational agents engage the learners in mixed-initiative exchanges, driven by scripted or intelligent dialogue engines. These agents may approximate conversational aspects of a human tutor, including a range of facial expressions, gestures, pointing, and of course, natural language articulation. Through these mechanisms, agents can guide instruction, explain system capabilities, and answer relevant questions. The inclusion of multiple agents affords modeling of ideal behavior, reflections on learner behavior, social interactions, and more natural articulation of learning strategies (Craig et al. 2015; Graesser, Li, & Forsyth, 2014; Johnson & Lester 2016). Agents can assume the role of experts in the target domain, tutors, or learning companions.

One example of intelligent conversational agents in ITSs has been *AutoTutor* and its family of descendant systems (Graesser, 2016; Nye, Graesser, & Hu, 2014). These systems have covered STEM topics such as computer literacy physics, biology, and scientific reasoning. Likewise, the systems *Betty's Brain* (Biswas et al., 2010), *Coach Mike* (Lane et al., 2011), *Crystal Island* (Rowe et al., 2011), and *Tactical Language and Culture System* (Johnson & Valente, 2009) have all demonstrated improved learning.

Investigations into the effectiveness of ITS approaches have demonstrated improvements over conventional learning approaches (including classroom teaching and unsupervised reading) with effect sizes that range from a marginal $d = 0.05$ (Dynarsky et al. 2007; Steenbergen-Hu & Cooper 2014) to a substantial $d = 1.08$ (Dodds & Fletcher, 2004), with most converging on relatively large values between $d = 0.40$ and $d = 0.80$ (Kulik & Fletcher, 2015; VanLehn, 2011).

Despite the empirically established benefits of the ITS approach, several factors have hampered wide-spread creation and adoption, including development time, cost, and requisite wide-ranging expertise (e.g., computer programming, artificial intelligence, computational linguistics, learning science, educational psychology, and domain expertise). There have been efforts to minimize these barriers and some modest progress has been made in authoring efficiency and speed (Sottolare et al. 2015). However, ITS development in the past has typically required substantial funding and sometimes multiple funding sources. This suggests the need for integrative cost-sharing approaches that have broader scope and impact. In this paper, we show how it is possible to leverage the progress of multiple teams and dramatically increase learning content.

Department of Defense Motivation

Recognizing the capabilities and advantages of the ITS approach, the US Department of Defense has historically encouraged innovation in ITS through grants and initiatives (Chipman, 2015). The Office of Naval Research (ONR) has a strong record of fostering ITS innovation. The Army Research Laboratory has cultivated the Generalized Intelligent Framework for Tutoring (GIFT; Sottolare et al., 2014, 2015) with the goal of providing a standardized platform to encourage creation and widespread adoption of interconnected computer-based instruction modules. Further, the Advanced Distributed Learning community (2016) has helped to develop and integrate standards, and the National Science Foundation has funded large-scale projects, including the Pittsburgh Science of Learning Center (Koedinger, Corbett, & Perfetti, 2012). Several initiatives within the Department of the Navy specifically motivate the creation of an integrated ITS which combines the approaches described above to provide learners with many pathways to relevant knowledge, skills, and abilities. We highlight three programs that have informed our approach and development of the complex learning platform described in this paper.

The ONR, through its STEM Grand Challenge, encouraged development of ITSs to increase STEM literacy, instruction, and career opportunities. Participants in the Grand Challenge were commissioned to integrate four ITSs on a new topic (electronic circuits) into a coherent platform that also included conventional learning resources. The resulting system, *ElectronixTutor* (Graesser et al., 2018), provides unprecedented breadth of pedagogical approaches to adaptive computer instruction. Further honing our approach is the Sailor 2025 initiative. According to its vision, sailors can engage at any time with the system to cover a wide range of electronics concepts at depths responsive to their military occupational specialty, platform, and ability, while also providing commanding officers with up-to-date learning records. Similarly, the Learning Continuum and Performance Aid (LCaPA) initiative is guiding a shift from an industrialized approach to education with one-size-fits-all pedagogy toward a personalized, learner-driven model that anticipates the needs of both the Navy and the individual sailor.

DEVELOPMENT

Learning Resources

The ITS learning resources on electronic circuits were developed from scratch in a two-year period and subsequently combined with conventional learning resources already in use by the Navy and civilian learning communities. Together, these resources address the needs articulated by the Navy for A-school training of avionics technicians or engineers. The resulting combined system also strives to align with the learning and technology standards articulated by the Army Research Laboratory and the Advanced Distributed Learning Initiative. The learning resources integrated into the common platform are presented in this section.

AutoTutor, developed at the University of Memphis, presents learners with two conversational agents that focus on reasoning and conceptual understanding through natural language interaction (Graesser 2016; Nye et al. 2014). A tutor agent asks difficult questions that encourage conceptual reasoning, followed by a multi-turn conversation that adaptively probes aspects of a complete answer that learners may have omitted. For example, if an ideal answer has five components but a learner only articulates three of them initially, the tutor agent uses hints and prompts to encourage the learner to express what they know about the other two, and makes corrections as necessary. A peer student agent provides flexibility in conversational roles and facilitates more natural exchanges. Initial questions can range from deep reasoning of broadly related concepts (e.g., what is the purpose of a transistor) to more specific aspects of a complex domain (e.g., what is meant by breakdown voltage of a Zener diode). The content and depth of the questions are selected on the basis of the learner's performance and psychological characteristics.

Dragoon, developed out of Arizona State University, focuses on mental model construction and simulation (VanLehn et al. 2016). Learners must manipulate aspects of a complex circuit diagram and demonstrate that variations in one parameter will change the behavior of the circuit as a whole. Dragoon provides difficult problems, incorporating both conceptual relationships and mathematical reasoning in a holistic model of complex circuits.

LearnForm, a platform developed by Raytheon/BBN, enables creation and delivery of problem-solving tasks. A learning task consists of an overarching problem statement, contributory multiple-choice questions, feedback on performance, and a summary of a complete correct answer. Learners are free to select problems in the generic LearnForm platform, but ElectronixTutor overlays task and learner characteristics to produce intelligent task selection.

ASSISTments, spearheaded by Worcester Polytechnic Institute, facilitates the on-line development of learning content, assessments, and other related technologies by instructors and other non-programmers (Heffernan & Heffernan, 2014). This platform provided the original learning management system for ElectronixTutor before it was migrated to the open-source Moodle platform. ASSISTments provides "skill builders" that give the learner drill and practice on the mathematics of basic electricity laws (Ohm's, Kirchhoff's).

BEETLE-II, a conversation-based ITS previously funded by the ONR, explores basic electricity and electronics (Dzikovska et al., 2014). The problems are on open and closed circuits and using voltage to find a circuit fault. This is a beginner-level interactive resource that was supplied by the Naval Air Warfare Center Training Systems Division.

Conventional, non-adaptive learning resources provide additional pedagogical content at relatively low cost. These static resources allow learners total control over their study, potentially helping those who prefer free selection, unguided exploration, and self-regulated learning. Static resources include the *Navy Electronics and Electricity Training Series* (U.S. Navy, 1998), which includes over 5000 pages of content which form the basis for Navy electronics technician training. Each major topic area also includes a summary constructed by domain experts that contain a few pages (2–5) of essential information, including diagrams and hyperlinks to related web-based references (e.g., Wikipedia).

Asking questions and receiving good answers is associated with learning gains, but learners often struggle to ask appropriate questions. A *Point & Query* facility (Graesser et al., 2018) combats this challenge. In *Point & Query*, learners can hover their mouse over a hotspot on an image (e.g., a resistor or capacitor), causing questions to pop up (e.g., "What is this part?"; "What is the function of this part?"). Mousing over one of the provided questions exposes the answer. Learners can then leverage common questions and answers, indexed to the relevant portion of the circuit

in question. Point & Query induces a dramatic increase in the number of questions asked to about 120 per hour, or approximately 700 times the classroom rate (Graesser & Person, 1994).

Together, these resources cover a wide range of topics in circuitry and electrical engineering. Beyond that, they allow learners to approach the same topic in different ways. Although each individual resource does not typically cover all of the available topics (AutoTutor being the broadest, covering 15), each topic includes at least two resources that learners can leverage to explore the avenue of understanding that suits them best. Further, beginning topics typically have more resources available (specifically, the easier, more fundamental problems provided by BEETLE and ASSISTments), as learners orient themselves to a new field. Integrating these resources into a single platform provides unprecedented breadth, depth, and flexibility.

Integration

Learning Standards

The resources listed above were designed to engage learners at myriad levels of analysis and methods of interaction. The resources substantially differ in content, detail, media, and instructional approaches, but at the same time there needs to be some principled foundation for recommending the particular resources at the right time for the right learner. The primary approach to the integration was to bind the resources through subject matter content at an intermediate grain size. More specifically, *knowledge components* (Koedinger et al., 2012) were adopted to form the basis of an interlingua that compares learner behavior across the constellation of learning resources. A knowledge component is defined by Koedinger et al. (2012) as “an acquired unit of cognitive function or structure that can be inferred from performance on a set of related tasks”. There is no standard way to specify knowledge components, but we adopted an intermediate-level grain size that proved to be functional. Each knowledge component in ElectronixTutor is specified as a topic-frame pair, where each topic is a concrete component in the curriculum (e.g., transistors, filters, PN junction), and each frame is the epistemic frame or schema (e.g., structure, function, behavior, parameter) specified by a domain expert. Within the epistemic frames, “structure” represents the components and terminals that a device has. “Function” is an understanding of the purpose of device components on successful device activities. “Behavior” represents the impact of the state of a device on its activities. “Parameter” represents the influence of quantities and values of variables on the device operations. These frames are theoretically assumed to be ordered on difficulty for mastery: structure < function < behavior < parameter. For example, we can examine the knowledge component “Diode_Behavior_Forward”. Its topic is “Diode” and its epistemic frame is “Behavior”. It represents the following ideas:

The diode only lets current flow in one direction through it, namely the direction that its triangle points. When current is flowing through it, the diode is said to be forward biased. When the diode is forward biased, then the diode has a very low resistance, about 100 ohms. Most resistors have a much higher resistance, so when a forward-biased diode and a resistor are in series the total resistance is pretty much the same as the resistor’s resistance. Thus, the amount of current that flows is determined by Ohm’s law ($V = I \cdot R$) where R is the resistance of the resistor. The bigger the resistor, the less current that flows.

Knowledge Component Uses in ElectronixTutor

In ElectronixTutor, knowledge components are used for multiple purposes, including (1) checking completeness of curriculum; (2) linking various learning resources; (3) identifying difficulty level of learning items; and (4) tracking learners’ progress. Completeness of a curriculum is critical to providing a comprehensive ITS. In ElectronixTutor, there are hundreds of learning items (i.e., a complete single task for a given learning resource, like a question in AutoTutor or a diagram in Dragoon). Learning items are mapped to curricula via knowledge components. The way we specify knowledge components provides a structural organization of learning curriculum. The mapping from learning items to knowledge components can clearly show the completeness of the learning curriculum and the repetition of knowledge components in items by use of a simple table.

Likewise, linking various learning resources (and integrating new resources as they become available) becomes relatively straightforward with knowledge components. This integration requires that a learning resource satisfies two requirements. The first one is simply a mapping from particular items to knowledge components. This is usually trivial for a content expert, even after the development of the learning resource. Regarding the second requirement, when a learner finishes an item, the learning resource can report a performance score on each associated knowledge component. This often involves the creation of wrapping code because the independently developed learning resources

often do not have a standardized assessment that is based on the adopted knowledge components. Performance scores are standardized on a scale from 0 to 1 that provides a common metric for all learning resources.

Item difficulty can vary significantly so there needs to be some comparative scaling. In ElectronixTutor, the process of calculating theoretical difficulty values begins by assigning difficulty values to each of the four categories of knowledge components. Structure, function, behavior, and parameter knowledge components are assigned respective difficulty scores of 0.25, 0.5, 0.75, and 1.0. Learning resources are also assigned difficulty values of 0.25, 0.5, 0.75, and 1.0 for BEETLE & ASSISTments, AutoTutor Knowledge Check questions, AutoTutor Deep Reasoning questions & Learnform, and Dragoon respectively. Each of the topics has an assigned difficulty that is also scaled between 0–1. Finally, the item’s difficulty is calculated as an average of its learning resource difficulty, the number of knowledge components associated with the item, and the difficulties of each knowledge component associated with the item. These theoretical difficulty values are used in lieu of empirical difficulty values that will be incorporated into ElectronixTutor after sufficient user data have been collected and analyzed via machine learning techniques.

Finally, knowledge components play an important role in learner modeling. Learners are modeled using several key metrics including: knowledge component scores, item scores, learning resource scores, topic scores, item completion, and item success, among others. A 0 to 1 metric is used in computing each of these scores.

Learning Record Store

ElectronixTutor has a Learning Record Store (LRS) that records all student learning progress. In particular, the LRS we use is Learning Locker, an xAPI-compliant LRS which is optimized for performance. Experience API, or xAPI, is a standard specification for capturing individual learner experiences in a consistent format; there are “statements” consisting of agents, verbs, objects, results, contexts, authorities, timestamps, and attachments. Each time a learner completes an individual learning item, a set of “SaveKCScore” statements is transmitted to the LRS. These statements contain relevant information for capturing learning progress, such as the score for each knowledge component associated with a learning item, the corresponding problem ID of the completed learning item, time taken on the learning item, and the unique ID of the learner whose progress is being tracked. There are two main ways we access the LRS. One is through the conventional xAPI RESTful interface; the other is the Aggregation API, which is unique to Learning Locker and offers an http wrapper around MongoDB’s powerful aggregation pipeline.

Recommender System

Learners can access learning resources in three distinct ways, each of which is located on the left sidebar of the interface (see Figure 1). First, at the top left, is the Topic of the Day, which is the primary topic for the student to focus on that day. This is ideally specified by the instructor, but if not, there is a default ordering which is based on Knowledge Space Theory (Falmagne et al., 2013) and the judgment of a subject matter expert. Second, a recommender system (described below) recommends three student activities considered by the system to be high priority for that learner. Lastly, learners can engage in self-regulated learning by clicking through the red “Navigation” menu at the bottom left. Here, the learner can select a topic and learning resource, with individual items generated by the computer.

Whereas the Topic of the Day is entirely instructor-centered, and the self-regulated learning is entirely learner-centered, the recommender system fits neatly between the two. It provides a list of three activities, but allows a choice, giving learners a sense of control without full autonomy. The recommender system recommends topics and learning resources based on the learner’s past long-term performance and psychological profile. For example, the system may recommend the student repeat a completed topic with poor performance, starting with an AutoTutor Deep Reasoning Question. Conversely, the student may have performed well in a topic, but performed poorly on (or did not attempt) a difficult learning resource (e.g., Dragoon). Here, the system can push the student by recommending the difficult resource. In another scenario, if the student is struggling with a particular Knowledge Component, the system will recommend a relevant AutoTutor Knowledge Check question or a Circuit Reasoning question.

The screenshot displays the ElectronixTutor interface. At the top, there is a navigation bar with the course title 'Electronics Tutor' and a search bar. Below this, a breadcrumb trail shows the path: Dashboard > My courses > Topics > Series/Parallel Combination > Conversational Reasoning > Conversational Reasoning 1. The main content area is titled 'Conversational Reasoning 1' and contains a question: 'Draw, if we want to increase the current of this circuit, how would we connect a resistor, labeled R4?'. The question is presented by a male avatar. To the right, a female avatar is visible. Below the question is a circuit diagram labeled 'Fig 1: Series-parallel circuit'. The circuit consists of a voltage source V_1 connected in series with resistor R_1 . This is followed by a parallel branch containing resistor R_2 . After the parallel branch, resistor R_3 is connected in series. A tooltip points to resistor R_2 with the text: 'What is this component? What is the function for this component? A resistor is used for voltage division.' Below the circuit diagram is a text input field containing the answer: 'We would connect the resistor in parallel with R1'. A 'Submit your Answer' button is located below the input field. On the left side of the interface, there is a navigation menu with sections for 'Topic of the Day' (Ohm's Law & Kirchoff's Law), 'Recommendations' (PN Junction, Op Amp, Diode Limiter & Clamper), and 'Navigation' (My courses, Topics, Grades, Ohm's & Kirchoff's Laws, Series/Parallel Combination, Topic Summary, Navy manual reading, Conversational Reasoning, Circuit Basics, Circuit Reasoning, Electronics Laws, Filters, P-N Junctions, Rectifiers, Power Supply, Diode Limiters & Clamper, Zener Diodes & Regulators).

Figure 1. The ElectronixTutor Interface during a Conversational Reasoning Question, with Point & Query

TESTING

Participant Populations

As mentioned earlier, each of the ITSs used as learning resources had been independently tested and validated in previous research prior to the development of ElectronixTutor (Graesser et al., 2018). We also conducted tests of some ITS modules in ElectronixTutor, but mainly to tune the subject matter content and test the usability on small samples of testers. For example, the AutoTutor main questions on electronics were posed to Amazon Mechanical Turk workers with a background in electronics to confirm clarity and level of difficulty. After these component validations, the complete, fully integrated ElectronixTutor system was presented to undergraduate electrical engineering students in beginner, intermediate, and advanced circuitry and electronics courses. Although participants had continuous access to the system, incentives were kept minimal to investigate voluntary engagement behavior. Participants in the beginner and intermediate courses were offered extra credit in their courses based on the time spent interacting with the system. We also informed all participants that future testing would be paid, but only for those who passed a substantial threshold of use. Students had to complete a 30-item pre-assessment before using the system. Out of four total courses, we obtained a sample of 19 students who completed the pre-assessment and at least one learning item.

Preliminary Results

The results from our sample were both encouraging and informative. On days when users logged in, they spent an average of 32.5 minutes on the site. Users completed 19 skill builder problems, 75 BEETLE-II problems, 400 Learnform problems, 128 AutoTutor conversations, and 37 Dragoon problems. They also read topic summaries a total of 71 times. The most popular topics were Series & Parallel Circuits and Ohm's & Kirchoff's Laws, with 434 and 163 items completed, respectively. All other topics had fewer than 50 completed items. Users completed 35 learning items on average, but this was significantly skewed by one user who completed 433 and three other users who averaged over 40 completed items. The median number of completed items was eight. In general, users did quite well on the attempted problems, with an average knowledge component score of 0.78 (this was computed using the mean of each user, so each user was equally represented). Overall, the fact that some users interacted with the system far more than we anticipated was extremely encouraging, and indicated they found the system valuable.

User Feedback

Although the individual learning resources have all undergone extensive testing and validation, the integrated environment was undergoing its first live testing. As such, feedback from the first batch of learners proved invaluable. The system provides the option of recording impressions, problems, or benefits of use via a built-in feedback page. This page, with an editable text field, records the topic and learning resource from which they came to enable troubleshooting at these more specific levels. Preliminary feedback has been generally positive, with learners appreciating the natural language interface of AutoTutor and the variety of resources available. Some reported slow-downs during transitions between learning resources. We identified this as an issue with how particular statements were saved in the database, and we accordingly made the necessary corrections. Other efforts such as containerization and migration to a dedicated server will further enhance the responsiveness and help optimize user experience.

CONCLUSIONS AND FUTURE WORK

Trends toward individualized computer-based instruction face obstacles of breadth and depth of quality material, along with siloed efforts that resist cross-platform interactivity. The combination of disparate complex learning environments, together with conventional instructional material, presents a substantial challenge for educators attempting to meet the needs of evolving pedagogical realities. Efforts by the Department of Defense to encourage innovative solutions demonstrate a clear priority from an organization with massive training and education responsibilities. The work detailed in this paper demonstrates that the creation of a quantitative interlingua (here based on knowledge components) can afford meaningful communication among independently created ITSs and static learning materials. Further, this communication opens the door to intelligent recommendations at the topic, resource, and difficulty frames of reference based on learner performance and characteristics. We view three accomplishments as our primary contributions to this field: first, the technical integration of disparate learning resources into a single, accommodating learning platform; second, the conceptual integration of those resources by means of learning standards; and finally, leveraging that environment and those standards to create adaptively intelligent recommendations for the learners.

While substantial quantitative data are not yet available to adequately validate the approach, preliminary data suggest that learners find utility in this type of diverse learning environment even when motivation to engage was minimal. Instructors at multiple institutions have granted permission to integrate this system into their courses, assuring motivated use that will test effectiveness relative to proper control conditions. We note that integration into the Navy's A- and C-school curricula would conform to this latter format as well. Pending the acquisition of such data, we anticipate answering a number of questions, including which resources learners prefer (remedial versus challenging; conversational versus graphic), how much learners trust recommendations versus self-direct their learning, and how learner characteristics influence these behaviors. Answers to all of these will substantially improve our understanding of ITS interaction generally and inform ITS designs in new domains.

The architecture and functionality of ElectronixTutor in many ways mirrors those of the Generalized Intelligent Framework for Tutoring (GIFT) (Hampton et al., 2018; Sottolare et al., 2014). Although the architecture of the former was created to meet specific functional challenges, the architecture of the latter was created to foster general, expandable functionality. Migrating ElectronixTutor to GIFT could produce benefits to both the theoretical and practical application of intelligently adaptive modular instruction. Reconciling ElectronixTutor's theoretical framework with the GIFT architecture would require standardization that would facilitate the inclusion of additional learning resources, both intelligent and conventional. This effort could substantially improve the scalability of ElectronixTutor while making it more accessible to a broad swath of Department of Defense communities.

Although the term "Intelligent Tutoring System" draws debate among practitioners as to what the qualifying characteristics include, no one contests the validity of applying the moniker when a system can independently improve itself. The application of machine learning techniques to the recommender system can continuously adjust difficulty ratings and identify the most effective progressions through course material as learners generate more data. This approach will update based on comprehensive learner behavior, helping to identify patterns that can be leveraged into iteratively more intelligent learner interaction. The system currently possesses the architectural capacity to implement machine learning improvement, and only lacks sufficient learner data to establish ideal parameters.

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