Creating an Advanced Pedagogical Model to Improve Intelligent Tutoring Technologies

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ABSTRACT

Computer-Based Tutoring Systems (CBTS) are effective learning tools with a high degree of customizability. However, their application in the training community is limited due to high development costs, limited reuse, and a lack of standards (Sottilare, et al. 2012). To remedy this issue, the U.S. Army Research Laboratory is developing an open-source modular program called the Generalized Intelligent Framework for Tutoring (GIFT). GIFT provides a set of tools to author, deliver, and evaluate intelligent tutoring applications. An essential component of GIFT is a domain-independent pedagogical module that manages instruction based on a learner's unique information. The purpose of this pedagogical module is to tailor and induce intervention via empirically-based generic instructional strategies. The goal of this research is to create an algorithm in the form of a decision tree within the pedagogical module, which will inform adaptation based on generalized characteristics associated with the learner and domain being trained.

The authors previously presented a list of learner characteristics (e.g., learner motivation, working memory capacity, prior knowledge, etc.) that form the basis of this pedagogical model development (Goldberg et al., 2012). For each identified variable, validated psychometric instruments were selected and threshold levels established (i.e., score designates high/low groupings). Based on this information, the authors developed an extensive database of empirically validated instructional strategies. Each strategy was mapped to the four categories of Merrill's (1994) Component Display Theory (CDT): Expository generality (general rules), Expository instance (specific examples), Inquisitory generality (recall knowledge), and Inquisitory instance (apply knowledge). This development resulted in a pedagogical model that provides recommended generalized strategies for incorporation in the CBTS authoring process. The authors will present work associated with the model development, highlighting a detailed use-case of its implementation within a specific training instance. In addition, the authors will also present the results from initial model validation.

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INTRODUCTION

In the military training community, there has been a call for point-of-need training in environments where human instructors are unavailable or unpractical to use (Sottilare et al., 2012). Past research has suggested that Computer-Based Tutoring Systems (CBTS) could be an effective training method when utilized properly (VanLehn, 2011). More specifically, Bloom (1984) stated that human tutoring has an effect size of d = 2.0 as compared to classroom teaching. CBTs or intelligent tutoring systems on average have produced an effective size of d = 0.31 (Kulik and Kulik, 1991; VanLehn, 2011). However, despite 50 years of research, CBTSs have not been widely adopted by the military training community or the general education system. According to Picard (2006), constraints such as high development cost, limited reuse capability, a lack of standards, and their inadequate ability to adapt to the users have severely hindered the growth of CBTSs. Specifically, the often complex and ill-defined military training environment has further hampered the usage of CBTS' applications in the military (Sottilare et al., 2012). CBTSs are often built as domain specific, one-of-a-kind solutions that teach specific knowledge areas. However, this type of framework makes reusing and restructuring a CBTS difficult. To minimize development cost and improve the capability of CBTS for reuse, the U.S. Army Research Laboratory is in the process of developing an open-source modular program called the Generalized Intelligent Framework for Tutoring (GIFT). Under the GIFT architecture, a set of tools is available for instructors to author, deliver, and evaluate intelligent tutoring applications. An essential component of GIFT is a domain-independent pedagogical module that manages instruction based on a learner's unique information. The purpose of this pedagogical module is to tailor and induce interventions via empirically-based generic instructional strategies. The goal of this research paper is to present GIFT's engine for Macro-Adaptive Pedagogy (eMAP), an algorithm in the form of a decision tree that is able to inform adaptation based on generalized characteristics associated with the learner and the targeted domains. In addition, the results of a preliminary validation study to exam the implementation of the eMAP are also included in this paper.

THE GIFT FRAMEWORK

GIFT Overview

The Generalized Intelligent Framework for Tutoring (GIFT) is an open-source architecture under development by the U.S. Army Research Laboratory and is the transition target for the work described. The framework is a domain-independent, service-oriented architecture that is designed to support the authoring, execution, and evaluation of empirically based pedagogical functions (Goldberg et al., 2012). Centered on information pertaining to an individual's Knowledge, Skills, and Abilities (KSAs), GIFT is intended to manage instruction by tailoring content and guidance around the strengths and weaknesses of a particular learner. To tailor instruction effectively, strategies need to be based on both historical information linked to a learner (e.g., trait-based information for macro-adaptation; Goldberg et al, 2012) and real-time interaction within the learning environment (i.e., state-based metrics related to performance and affect for microadaptation). This enables GIFT to tailor instruction prior to system interaction based on what is already known about the learner, and to adapt instruction in real-time based on progression and performance within a lesson.

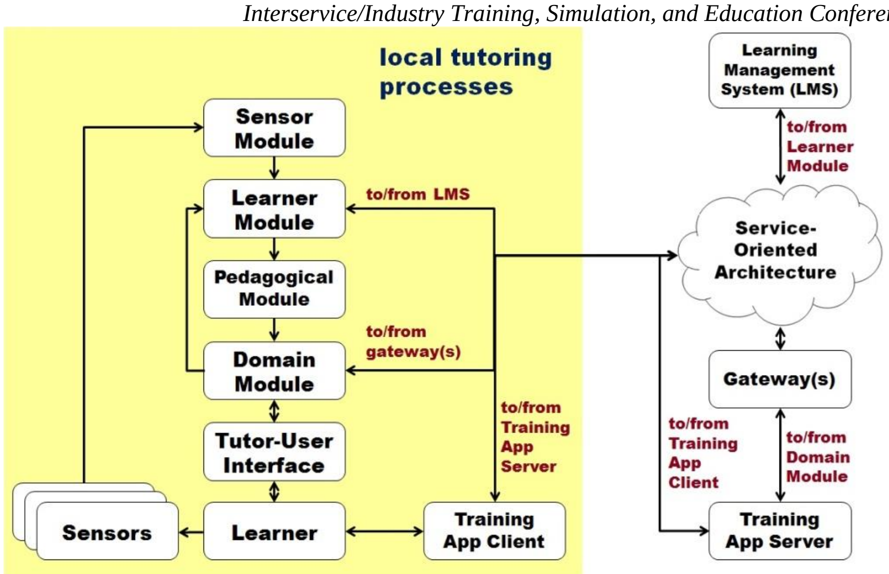

Figure 1. Generalized Intelligent Framework for Tutoring (GIFT)

To achieve these capabilities, GIFT is modularly designed with components common to all CBTSs: (1) a Learner Module comprised of information on individual difference variables used to inform adaptation and performance states, (2) a Pedagogical Module used to manage strategy/adaptation selection based on the individual's traits and performance states received from the Learner Module, (3) a Domain Module that directs the specific training content and strategies to carry out along with models of expert performance for assessment purposes, (4) a Sensor Module used to monitor cognitive and affective states that impact learning (e.g., engagement, boredom, confusion), and (5) a Learning Management System (LMS) to store and collate learner profiles based on outputs from the Learner Module (See Figure 1; Sottilare et al., 2012). Each module performs separate processes that are associated with the tutoring effect chain (Sottilare, 2012), where data are used to infer learner states that manage the selection of instructional strategies intended to influence performance and retention of domain-relevant content (see Figure 2).

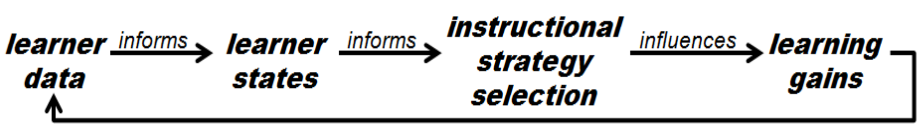

Figure 2. Adaptive Tutoring Learning Effect Chain

As GIFT is designed to be domain-independent, defining instructional strategies creates a unique challenge as their context must be generalizable enough to be applied across multiple domains. Because of this, distinctions were made between strategies and tactics in that strategies provide high-level pedagogical recommendations (e.g., use highly visual content), while tactics specify the content or adaptation to implement based on the domain being instructed (e.g., play video on interrogation techniques; Goldberg et al, 2012). The pedagogical module uses state information provided by the learner module to determine when a GIFT intervention/adaptation is required and available trait information to select specific strategies intended to maximize the effectiveness of the instructional session. For each strategy identified in the pedagogical module, there must be a defined tactic in the domain module that will be implemented when called upon. To ease this burden, GIFT's pedagogical module provides a generalized strategy along with assistance on how to author a tactic based on the context of the recommendation.

With the pedagogical module being comprised of empirically based strategies found to influence learning outcomes, data must be established to manage strategy selection based on individual differences associated with a data variable of interest. As reported in Goldberg et al. (2012) an extensive literature review of instructional strategy focused research was conducted to identify methods found to consistently impact learning outcomes and to determine the variables that can be used as selection criteria. This requires three components to be in place. First, individual difference variables that will be data inputs to the pedagogical module must be identified. These variables were derived from the literature and are composed of trait characteristics that are rather static in nature (e.g., motivation, self-efficacy, memory capacity). Second, there must be instruments available to collect data to inform trait values. These values are what ultimately dictate the selection of strategies among a bank of choices. The third component is the inclusion of metadata to form generalized descriptors of content and interventions that act as the basis for selection criteria in terms of choosing specific strategies among a bank of choices.

The Component Display Theory

The eMAP adopted the CDT as its grounding theory. CDT is a set of concepts that describes the conditions, methods, and outcomes of instruction (Merrill, 1994). It helps in the organization of instruction, along with the sequencing and presentation of content appropriate for learners. Furthermore, CDT prescribes relationships that can be used to guide the design and development of learning activities. Thus, CDT was chosen to simplify the development of instruction in GIFT as it provides the basis for appropriately selecting instructional modules and their organization (Merrill, 1994).

The CDT model has several unique features that could significantly benefit the pedagogical module (Merrill, 1994). For instance, it can be used to guide the design and development of learning activities; it provides individualized instruction in less structured environments; it allows learners to have control over the content; the strategy components are chosen to fit learners' momentary state aptitudes and their more permanent trait aptitudes; and it prescribes instructional conditions based on the types of the desired learning outcome. These instructional conditions, known as CDT's Presentation Forms, provide the basic building blocks for the instructional strategies present in the eMAP. CDT indicates two paths when it comes to content as depicted in the Primary Presentation Forms (See Figure 3): Content can be presented (expository); or the instructor asks the student to remember or use the content (inquisitory). The content can represent a general case (generality) or it can represent a specific case (instance). Therefore, instruction can be divided into four categories: Expository generality – present a general case (Rule); Expository instance – present a specific case (Example); Inquisitory generality – ask the student to remember or apply the general case (Recall); and Inquisitory instance – ask the student to remember or apply the specific case (Practice). These four categories can be used as high-level metadata descriptors to label training content, with each category applying different pedagogical practices inherent to the learning process. Therefore, instructional strategies can be explicitly defined and categorized within each component of the CDT. This association allows an instructional designer to understand what a piece of content is intended to provide in a lesson context (i.e., this video provides an example for enabling objective x), and further instructional strategies can be defined to inform when this piece of material is most suitable for use. With a framework for organizing content and applying metadata descriptors, a model is required to determine selection criteria and to perform conflict resolution.

CDT Model
The Primary Presentation Forms

Content Mode	**Generality**	*Rule*	*Recall*
	Instances	*Example*	*Practice*
		Expository	**Inquisitory**

Presentation Mode

Figure 3. The Component Display Theoretical Model

The Decision Tree

This research effort created an algorithm in the form of a decision tree for authoring the eMAP within GIFT's pedagogical module, which informs adaptation based on general learner characteristics and information about the domain being instructed. Specifically, the decision tree informs the selection of instructional strategies based on known information about the learner (e.g., learner motivation, learning style, previous experience, etc.). The resulting strategies were identified through an extensive literature review of empirically based research, in an attempt to produce a list of commonly applied strategies found to reliably impact learning outcomes. These strategies were analyzed and classified into the following learners' characteristics: learner motivation, cognitive/learning styles, prior knowledge/experience, learner ability, etc) (see Goldberg et al., 2012 for full list of sources of adaptation). Subsequently, they were categorized into Rule, Example, Recall, and Practice based on the CDT. Below is an illustration of the strategies appropriate for learners with low motivation (see Figure 4). The resulting strategies identified for a specific learner serve as inputs to the domain module for selection of an explicit tactic to implement for a lesson (see Goldberg et al, 2012). Essentially, the eMAP provides individualized strategy recommendations for selection or creation of content within each quadrant of the CDT. During its initial development, a preliminary study was executed to serve as design guidelines in implementation and to assess the effect of the decision tree in a training context. The first iteration of the eMAP module is available is the current publicly available release of GIFT.

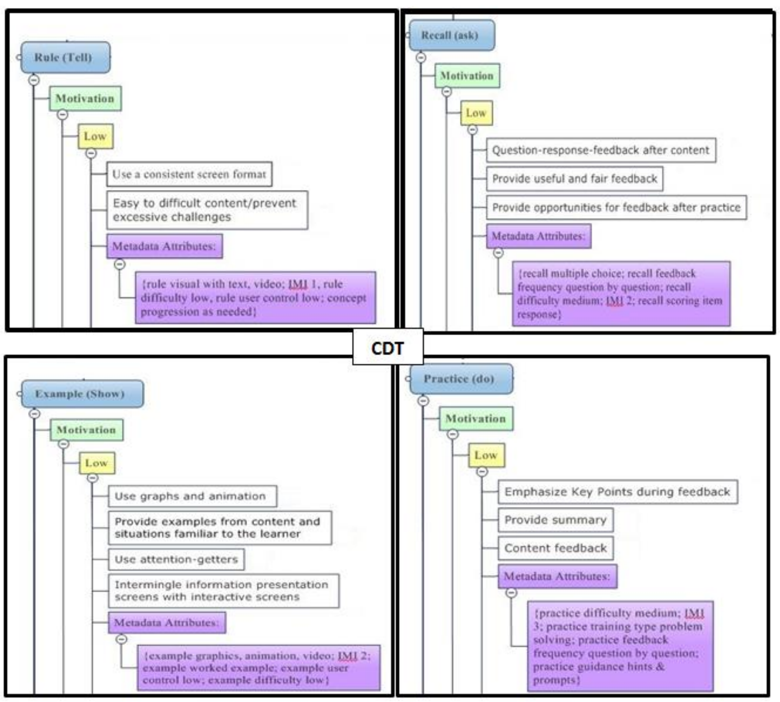

Figure 4. A Sample of the Decision Tree

A PRELIMINARY STUDY TO EXAMINE eMAP IMPLEMENTATION

The present study was intended to assess whether a course that was customized for an individual based on his or her motivation level (one of the targeted learner characteristics of the pedagogical module) would yield superior learning outcomes than a training course that was designed for the general class. For this study, three versions of land navigation course content were used. The control group course content was directly adopted from an Army land navigation course. The experimental content had two versions: high motivation learner course content and low motivation learner course content. These two courses were developed based on the same Army land navigation content, but integrated training strategies from the proposed eMAP that were more suitable for either high motivation learners or low motivation learners. Detailed description regarding course content and the grouping of participants can be found in the material section of this paper. It was hypothesized that participants in the experimental groups (high motivation learner and low motivation learner groups) would perform significantly better than the control group.

To investigate whether utilizing instructional strategies to accommodate individual differences (i.e., learner motivation) could produce better learning outcomes, the study employed a mixed between-within group experimental design. The first Independent Variable (IV1) was the different types of groups: the control group and the two experimental groups (high motivation learner and low motivation learner groups as deemed by the Motivation Strategies for Learning Questionnaire). The second Independent Variable (IV2) was test types: pretest and posttest. The Dependent Variable (DV) was students' performance on the baseline knowledge assessment test and the post knowledge test. Performance was measured by the percentage of correct answers on both tests.

A total of 30 participants were recruited for this experiment (14 males and 16 females), with age range between 19 and 38. They were recruited from the student body of the University of Central Florida. Monetary compensation was offered to participants as recruitment incentives. Additional demographic information can be found in Table 1. Out of the 7 participants who reported to have previous experience with land navigation, two participants reported that they have self-taught themselves map reading as a hobby, one participant performed as a navigator for her cross-country racing team, and one participant attended geography classes that taught map design. This data was used to exam potential correlations with participants' test performance.

Table 1. Demographic Information

	Control Group	Experimental Group – Low Motivation	Experimental Group – High Motivation
N	10	9	11
Age	19-38 years	21-38 years	19-34 years
Gender	F = 7; M = 3	F = 5; M = 4	F = 4; M = 7
Average Years of Education	15.8 years	14.4 years	15.1 years
Numbers of Participants with Previous Experience on Land Navigation	2	2	3

Materials

The Motivation Strategies for Learning Questionnaire

The Motivation Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991) is a self-report instrument designed to assess college level students' motivational orientation and their use of different learning strategies for an academic course. It has two sections, a motivation section and a learning strategies section. Since the scales in the MSLQ were designed to be used either as a whole or used separately, the present study only used the motivation section to assess students' motivation towards a land navigation course. Students rated themselves on a 7-point Likert scale from "not at all true to me" to "very true to me". The total points were added together to determine a participant's motivation level. The present study set 150 points as the threshold to determine if the participant was motivated to learn about land navigation. If a participant scored higher than 150 points, he/she was assigned to the high motivation experimental group. An individual who scored equal or lower than 150 points was assigned to the low motivation experimental group. To score higher than 150 points on the motivation section of the MSLQ, participants would rate themselves as 5 or above on each of the items.

The Knowledge Test (Baseline and Post)

The knowledge test consists of 26 questions (22 multiple-choice questions, three short answers, and one fill-in-the blank item) assessing participants' knowledge on land navigation. The multiple choice questions are worth one point each. The short answers are five points each, and the fill-in-the blank question is worth three points. The baseline test and the posttest contain the same questions but in different orders. The knowledge test was graded based on the percentage of correct answers.

The Self-guided Computer-based Course

The self-guided computer-based course was developed in MS Office Power Point. The lesson content was composed of materials for training basic land navigation skills linked to map reading and terrain association, and the course was configured into three versions. For the control group, the content was directly adopted from a land navigation course from the Army using its original slides and lecture notes. For the experimental groups, using the Army land navigation course as a foundation, the low motivation learner group course was developed based on the instructional strategies from the eMAP. For example, low motivation learners may benefit from using consistent screen format (Song and Keller, 2001), using graphs and animation (Mayer and Gallini, 1990), and using examples from content and situations familiar to the learner (Song and Keller, 2001). Thus, the computer-based course for the low motivation learner course uses a consistent presentation format, contains abundant pictures and graphs, and utilizes examples that are relatable to the learner. A recording of an instructor was also used to accompany each slide to help low motivation individuals pay attention to the course content (see Figure 5). Similarly, the high motivation learner group content was also created based on instructional strategies derived from GIFT's pedagogical module. For instance, learners with high motivation have been found to learn better when the course content contains rich linking technologies (Shin, Schallert, and Savenye, 1994), uses fewer graphics (Mayer and Gallini, 1990), and gives user control of navigation and pacing of navigation (Bill, 1990). Therefore, the computer-based course for high motivation learners include additional reading materials via web links, uses less pictures and graphs, and enable users to move through the course at their own pace (please see Figure 6 for content sample). Much of the previous research informing the eMAP is based on studies conducted over a decade ago. With the testbed component provided by GIFT's modularity, the architecture can support reexamining many of the relationships found from earlier work for validation purposes within more technologically advanced training environments.

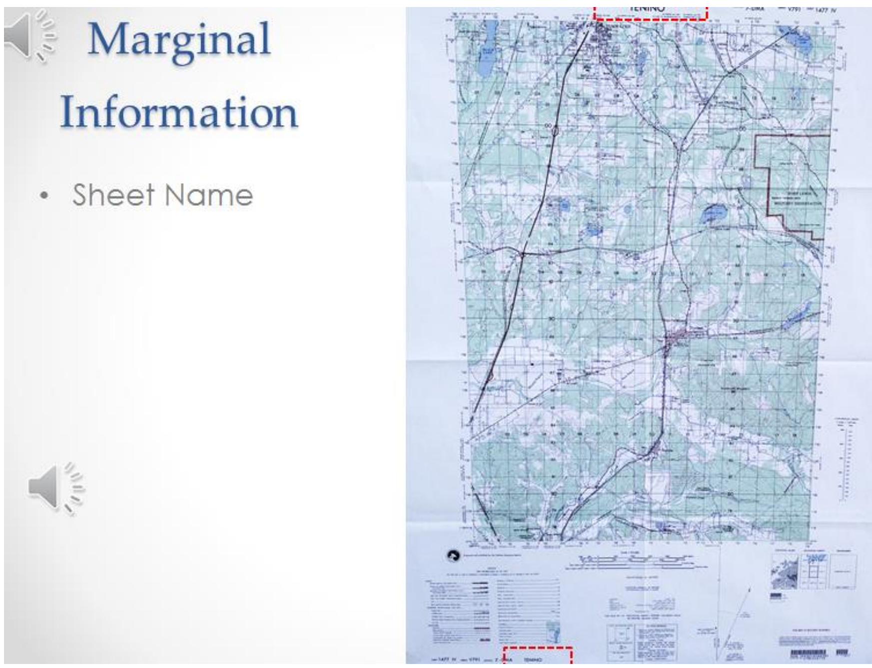

Figure 5. Low motivation learner course content sample

Figure 6. High motivation learner course content sample

Feedback Questionnaire

The feedback questionnaire consists of 15 questions. The first 10 items asks participants to rate their experience of the course on a 5-point Likert scale from "strongly disagree" to "strongly agree". Few examples of these items include "Navigating through the course was easy", "I enjoyed the instruction", and "the course materials were engaging." Item 11 to 15 are short answer items. Participants were asked to answer each question in one or two sentences. Few examples of these items are "Which aspects of the course contributed the most to your learning and why?" and "Has the course helped you to improve your skills?"

Procedure

Participants were randomly assigned to either the control or the experimental conditions. Upon arrival, participants were asked to read an informed consent document and given opportunity to ask questions prior to proceed to the study. All participants received a demographic questionnaire, a motivation questionnaire, and a baseline knowledge test on Land Navigation (pre-test). Then, the control group participated in a 45-minute self-guided computer-based Land Navigation course (the control group version) using a Dell laptop with 15-inch display. As for the experimental groups, depending on their scores on the Motivation Strategies for Learning Questionnaire, participants were assigned either to the high or the low motivation group. The high motivation group received the high motivation learner course content and the low motivation group received the low motivation content via the same Dell laptop computer. Both low and high motivation courses were 45-minutes long. When participants (experimental and control groups) completed the self-guided computer course, they received a post-training knowledge test and a feedback questionnaire which asked them about what they liked and disliked about the course.

Results

Analyses were conducted using SPSS 20.0 for Windows. An alpha level of .05 was used for all analyses. Before analyses were performed, the data was screened for any potential issues that could affect the results of the statistical analyses (i.e. transcription errors, missing data, etc). The log files were individually examined to ensure the data was valid and complete for proper analysis.

Correlations

Since Motivation was the learner characteristic selected for this study, a Pearson correlation test was conducted between learner motivations and the Knowledge test performance to examine the relationships among test performances and learner's self-reported motivation levels. There was a significant positive correlation between learner's motivation and the baseline knowledge test scores, $r = .397$, $p < .05$. The results also showed a strong correlation between learner's motivation and post-knowledge test scores, $r = .459$, $p < .05$. These two correlations suggest that motivation is indeed a critical learner characteristic that could influence learning outcomes. In addition, a significant positive correlation between prior experience with land navigation and the baseline knowledge test scores was also found, $r = .393$, $p < .05$. However no significant correlation was observed between previous experience and the post-knowledge test scores, thus participants who reported to have previous experience in land navigation were not treated differently from the rest of the subjects. It may also signify the effectiveness of the training materials, in that novices with no prior experience produced performance scores not significantly different from those subjects with previous exposure to the training domain.

Performance Outcomes within Groups

Three separate paired-sample t-tests were conducted to compare participants' performance from the baseline knowledge test to the post-knowledge test for the high motivation, the low motivation, and the control group. For the high motivation group a significant difference was found, $t(10) = -10.71$, $p < .000$. Participants scored significantly higher on the post-knowledge test than the baseline test. Similarly significant differences between the baseline knowledge test and the post-knowledge test were also found for the low motivation group, $t(8) = -2.84$, $p = .022$, and the control group $t(9) = -6.28$, $p < .000$.

Performance Comparison between Groups

A one-way between-group ANOVA was conducted to examine the performance differences on the post-knowledge tests among the high motivation, low motivation, and control groups. There was a statistically significant difference among the three groups, $F\ (2, 27) = 7.00$, $p = .004$. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for the high motivation group was significantly higher than the low motivation group. The control group also performed significantly better than the low motivation group on the post-knowledge test (see Table 2 for average group means on the post-knowledge test). The performance differences between the high motivation group and the control group were not significant. No significant performance differences were found among the three groups for the baseline knowledge test.

Table 2. Knowledge Test Percentage Scores for Each Groups

	High Motivation Group	Low Motivation Group	Control Group
Baseline Knowledge Test	*M* = 24.78 % (*SD* = .06)	*M* = 22.78 % (*SD* = .06)	*M* = 26 % (*SD* = .07)
Post-Knowledge Test	*M* = 51.14 % (*SD* = .10)	*M* = 33.33 % (*SD* = .10)	*M* = 46% (*SD* = .12)

Feedback Outcomes

No significant differences were found among the three groups for the first 10 items of the Feedback Questionnaire (all $p > .05$). However, it is worth noting that the high motivation group rated most of the questionnaire items higher (in the 4 range) than the other two groups. The low motivation group rated most of the items the lowest (in the 3 range). For the open ended questions, item 13 asked participants "if you could change this course, what changes would you make?" High motivation group preferred "More quizzes" and "use more user controlled interaction". The low motivation group would like to see "more examples, graphics, and videos." As for the control group, they wish they could have "animations", "some practice", and "examples", which were part of the high and low motivation groups' content, but wasn't provided for the control group.

Table 3. Mean Feedback Outcomes

	High Motivation Group	Low Motivation Group	Control Group
	1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree		
1. Navigating through the course was easy to understand.	4.27	3.67	3.9
2. The flow of the course was satisfactory.	3.91	3.44	3.8
3. I enjoyed the instructions.	3.82	3.33	3
4. The course materials were understandable.	4	3.89	3.7
5. The course materials were engaging.	3.36	3.44	3.5
6. There was appropriate feedback throughout the course activities.	4	3.11	3.1
7. The instruction kept my attention.	3.55	3.56	3.1
8. The combination of audio, pictures, and text was helpful in understanding course concepts.	4.09	4.22	4
9. I found the example to be relevant and meaningful.	4.18	3.33	4
10. Overall, how would you rate the course?	4.09	3.22	3.6

Discussion

All three groups showed significant improvement from the baseline knowledge test to the post-knowledge test. These results suggested that regardless of which group the participants were in, they all improved significantly from the baseline to the post-test.

When comparing the post-training outcomes across the three groups, the high motivation group and the control group performed significantly better than the low motivation group. This result may suggest that Motivation as a learner characteristic can critically influence, as well as predict, training outcomes. For this study, the high motivation group scored significantly better than the low motivation group. This result supported the early hypothesis that the high motivation would excel when proper instructional strategies were used to construct the course. However, it was not expected that the control group also performed significantly better than the low motivation group. Further analysis showed that 7 out 10 participants in the control group were high motivation learners (they scored above 150 points on the MSLQ). Because of this high motivation factor, they may learn better than the low motivation group. Further evidence could be seen via the correlation between learner motivation score (from the motivation questionnaire) and the knowledge test outcome. Strong positive correlations were found between motivation scores and baseline and post knowledge test performance. As for low motivation individuals, the results of this study suggested using motivation training strategies alone may not be enough to boost training effectiveness. Adding more comprehensive training strategies that deal with other learner characteristics may be more effective at improving low motivation learners' training outcome. In addition, interaction with training content over a more sustained period of time that represents a real-world course may influence performance outcomes.

As for the feedback questionnaire outcomes, there was an interesting trend with the participants' response from item 1 to item 10. Although not statistically significant, the high motivation group rated most favorably regarding their land navigation course as compared to the low motivation group who rated least favorably toward their version of the course. These results followed the same pattern as their post-knowledge test performance where the high motivation group performed the best and the low motivation group performed the worst. In addition, when participants were asked "if you could change this course, what changes would you make?", the high motivation group asked for more quizzes and more user controlled interaction, whereas the low motivation group would like to see more examples, graphics, and videos. These responses further suggest that the instructional strategies adopted for this study matched the students' preferences. The approach in which the eMAP recommended strategies were translated in domain tactics should be further assessed to determine if the resulting course met requirements linked to a strategy's description. Identifying the optimal approach for authoring domain specific implementations of an eMAP instructional strategy is an area of research that needs further exploration and refinement. Its implementation across more interactive training systems must also be examined.

CONCLUSION

The goal of this paper was to present the GIFT eMAP, an algorithm in the form of a decision tree within the pedagogical module. The decision tree involved many learner characteristics derived from empirical literature, which produces training strategy recommendations to target each learner variable identified. A preliminary validation study was conducted to exam one of these characteristics – learner motivation. The results suggested that learner motivation was a critical factor to consider when designing CBT courses: high motivation individuals may excel by introducing appropriate motivation training strategies alone. In contrast, low motivation learners may require a combination training strategies that target multiple learner characteristics (i.e., learner style, prior experience, knowledge type, etc.). Future studies are needed to investigate how learners' performance changes when training strategies for a combination of learner characteristics were introduced. Further exploration in the various applications used for education and training must also be performed to identify variations in strategy execution.

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