Multi-level User Modeling in GIFT to Support Complex Learning Tasks

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INTRODUCTION

Open-ended computer-based learning environments (OELEs) are user-centered. They present users with complex problems to solve, and a set of tools and resources that support the problem-solving task. While problem solving, users typically explore multiple solution approaches, and assess their evolving solutions to make sure they are making progress toward their learning and problem solving goals. In general, OELEs focus on developing users' (1) cognitive skills, (2) metacognitive processes and (3) problem solving strategies that go beyond the acquisition of domain-specific cognitive skills (Hannafin et al., 1994). These environments make high cognitive demands on users, and promote the development of strategies and metacognitive processes that can support planning, monitoring, and self-evaluation processes.

Novices often have difficulties in making progress when working in OELEs. To help such users with personalized and adaptive feedback, our goal is to create more detailed user models in the Generalized Intelligent Framework for Tutoring (GIFT) system (Sottilare et al., 2012), to support analysis of users' cognitive, strategic, and metacognitive processes as they work on learning or training scenarios. Previous approaches for providing feedback to users primarily focused on their performance when applying cognitive skills to solve a problem (Lester et al., 2014; Kulik & Fletcher, 2016). On the other hand, our approach dives deeper into the users' intentions when they work on the system. To interpret users' actions in context, we have developed a multi-level task modeling approach that specifies the cognitive skills and processes that helps us interpret user competence and behaviors as they work on their learning and problem solving tasks (Kinnebrew et al., 2016).

In this paper, we apply our user modeling framework to an OELE called UrbanSim (McAlinden et al., 2008), a turn-based simulation environment, where the trainee plays the role of a commander directing counterinsurgency (COIN) efforts in a Middle Eastern region. U.S. Army manuals (Nagl et al., 2005) discuss the strategic and operational implementation of COIN operations as including three phases: Clear, Hold, and Build (CHB). The idea is to deal with insurgents and empower Host Nation (HN) security and capacity building in service of the local population. In the UrbanSim environment, the officer trainee, acting on the Brigade commander's intent, analyzes the current state of the region, and performs activities directed to defeating the insurgents, while increasing the level of population support and facilitating self-governance and economic independence for the area. Trainees have access to political, economic, military, and infrastructure information about different regions in the area of operations (AO). More specifically, this also includes intelligence reports on individuals and groups, information on the stability of each region, and economic, military and political ties among their leaders.

The user model for the UrbanSim environment in GIFT is developed by considering the users' (1) proficiency in relevant domain tasks, and (2) their learning behaviors, i.e., the approaches they adopt in selecting, executing, and sequencing their tasks to achieve their learning and problem solving goals. Users' activities and actions on the system are collected from log files generated by the UrbanSim system, and interpreted by the log parser for analysis in the GIFT environment (Segedy et al., 2015). The proficiency of users in domain-specific task is measured by their ability to operationalize the mission goals, which are described by six Lines of Effort (LOE) measures. The six LOEs corresponding to the primary goals of most counter-insurgency operations are (1) Civil Security, (2) Governance, (3) Host Nation Security Forces, (4) Essential Services, (5) Information Operations, and (6) Economics. Related performance measures that can be extracted from the UrbanSim log files include: (1) Population Support, (2) Political, military, economy, social, information and infrastructure (PMESII) values of each region in the AO, (3) Military Power (MP) of the insurgents groups and the HN security force, (4) Coalition Support (CS) of individuals and tribes in the regions, (5) Effectiveness (EF) of utilities such as water storage unit, sewage treatment plant and trash depot in supporting the population, (6) Capacity (CA), that is the state of operations of infrastructures such as airport, hospitals and school.

In addition, we also analyze and interpret a set of strategies that we believe will further help us characterize the users' problem solving and decision making approaches, and their performance in the UrbanSim environment. The ability of the users to strategically implement the CHB doctrine is UrbanSim specific, but the other strategies: Situational Awareness (SA), Tradeoff Analysis (TA) and Second and Third order Effects (STE) of actions, are more general, and very likely apply to other problem solving and decision making scenarios. In GIFT, we compute users' proficiency in each strategy by using their links to the relevant UrbanSim activities and actions, as well as users' relevant performance measures (see last paragraph) provided by the UrbanSim system. The UrbanSim user model was developed by performing task analysis, consulting knowledgeable experts, and by analyzing users' interactions with UrbanSim from research studies that we conducted in past two years. In this paper, we will present our approach and demonstrate the effectiveness of the user-modeling scheme in providing instructional feedback to the users.

PROPOSED USER MODEL IN GIFT

Our proposed user-modeling framework implemented in the GIFT framework is illustrated in Figure 1. We have developed a three-tier hierarchical user model for monitoring and capturing users' cognitive skills, problem-solving strategies, and their metacognitive processes within the GIFT tutoring framework. The bottom layer of our user model derives information from logs of user activities collected from the training environment (e.g., UrbanSim).

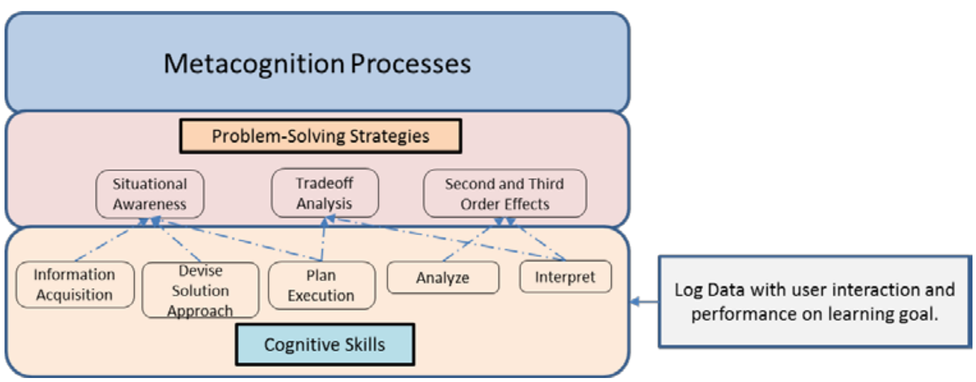

Figure 1. Three-Tier Hierarchical User Model

The middle layer of our user-modeling framework captures users' proficiency on problem solving strategies, which represent meaningful sequences (combinations) of cognitive skills, and provide the link to higher level tasks and goals that the user is trying to accomplish (Kinnebrew, et al., 2016), e.g., clear the area of insurgents to help establish local governance. The top layer captures users' proficiency on metacognitive processes that considers the users' intent in using a skill or strategy, as well as their monitoring, evaluation, and reflection behaviors as they work on the system. Strategies comprise an important component of metacognitive knowledge; they consist of declarative, procedural, and conditional knowledge that describes its purpose and when and how the strategy should be implemented (Schraw et al., 2006). In other words, we conjecture that strategies are an important component of the planning and evaluation phases in metacognition. An important goal that we have adopted in our work is to monitor and infer users' strategies as they work on complex open-ended problems, and provide adaptive support to help them improve their overall performance in their problem solving tasks. Problem solving strategies and metacognitive processes should be defined and apply generally across problem solving tasks. Therefore, we have designed the top layers of the user model to be accessible across different training environments that may be linked to GIFT.

A Hierarchical Task Model

Our OELE task model in GIFT is represented as a directed (acyclic) graph, which provides a successive, hierarchical breakdown of the primary tasks into their component subtasks in the OELE. At the lowest levels of the hierarchy, the tasks are linked to the observable actions in the OELE. The top level of the model identifies the three broad classes of OELE tasks related to: (1) information seeking and acquisition, (2) solution construction and refinement, and (3) solution assessment. Each of these task categories is successively broken down into three levels that represent: (1) general task descriptions that are common across many OELEs; (2) learning environment specific instantiations of these tasks; and (3) observable actions in learning environment through which users can accomplish their tasks.

Implementation of Three-Tier Hierarchical User Model in GIFT

The GIFT environment consists of three primary modules: (1) a user module, (2) a domain module, and (3) a pedagogical module. The domain module contains the domain-specific knowledge file (DKF), which defines (1) the course structure, (2) tasks, (3) concepts, (4) priorities and conditions to assess users' correct application of the concepts, and (5) instructional strategies to provide feedback or adaptive content to the user. In GIFT domain module, the concepts and condition to assess those concepts are represented as flat computational structure. GIFT concepts are assessed using the following performance metrics: (1) *Assessments*, measured as Below, At, and Above Expectation, (2) *Competence*, a value that captures the users' competence on the concept ranging between [0.0, 1.0], (3) *Confidence*, a value that represents the system's confidence in the assessment ranging between [0.0, 1.0], and (4) *Priority*, a unique value that defines the importance of a concept compared to the other concepts, and it is used by the instructional strategy handler to select the concept on which the system provides feedback.

To study how a user's competence evolves as they work on their tasks, we have added a performance metric to GIFT called *Trend* whose values range between [-1, 1]. In our work, we have adopted a simple trend measure that is computed over the user's last two turns.

$$\text{Trend} = Max\ ((P_i - P_{i-1}), (P_{i-1} - P_{i-2})) \qquad (1)$$

In order to implement, test and validate our proposed user model shown in Figure 1, we modified the GIFT DKF to represent the multiple concept types as a hierarchical structure. The modified GIFT DKF structure is shown in Figure 2. To measure the users' competence on cognitive skills, problem-solving strategies and metacognitive processes, we apply a bottom-up computational approach. First the users' performance on cognitive skills is computed from the parsed data extracted from the log files. The relevant user proficiencies on cognitive skills are then aggregated to derive the competence, confidence, and trend values for problem-solving strategies, which in turn forms the basis for computing these values for metacognitive processes.

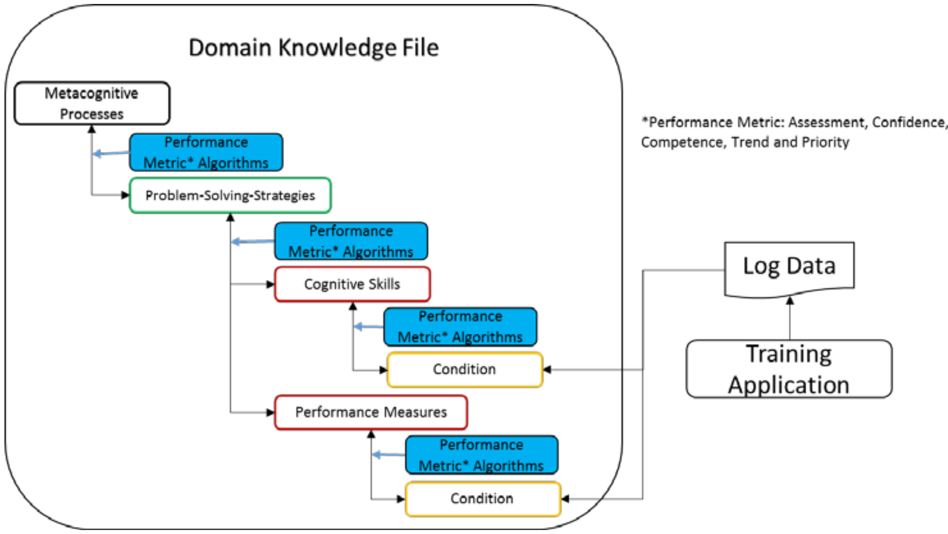

Figure 2. Implementation of Hierarchical User Model in GIFT

Our instructional strategy algorithm builds on this hierarchical structure and the performance metrics that we derive for each level. The algorithm analyzes the performance metrics top-down on the hierarchical structure, starting from the metacognitive level. It checks the competence and trend values of its child nodes (i.e.), the strategy nodes and picks the child node that has the least competence and a negative or flat trend. Then the algorithm repeats the analysis on its child nodes (cognitive skills). If the user is deficient in cognitive skills (i.e., their performance values for cognitive skills are below a threshold), the algorithm will pick one of the cognitive skills for feedback, otherwise, it focuses on the higher-level selected strategy for feedback. If the user has shown sufficient proficiency at the strategy level, then the algorithm selects a metacognitive process node for feedback.

Overall, this hierarchical user modeling structure and corresponding instructional algorithm has significant advantages. First, it explicitly captures the different processes that are important for learning decision-making and problem solving, and the relations between these processes. As a result, problem-solving strategies and cognitive skills are distinguished from domain specific skills, and they can be used across different learning and training systems that are linked to GIFT. More sophisticated instructional strategies can be implemented by combining the bottom-up and top-down analyses, allowing for more accurate assessments of the users, and increasing the scope of the feedback that may be provided to the users. We demonstrate some preliminary work that shows the effectiveness of our approach, but hope to demonstrate the full capabilities of this approach in future work.

IMPLEMENTATION OF THE USER MODEL FOR URBANSIM

In UrbanSim, the overall progress toward meeting COIN goals is represented by an aggregate measure called the Population Support (PS). Population support is derived from the coalition support in the regions for the U.S. armed forces. Users' adherence to the U.S. Armed forces Brigade Commander's intent or goals for the counterinsurgency operations, are measured as six Lines of Effort (LOE) scores. The LOE values are an aggregate of the Political, Military, Economic, Social, Information, and Infrastructure (PMESII) scores associated with each region in the area of operations (Tscholl, et al., 2016 & Tscholl, et al., 2016b).

As discussed earlier, user behaviors in the UrbanSim environment are derived from their interactions with the environment captured in the form of log files. To interpret users' activities in UrbanSim within the GIFT tutoring framework, we classify their interactions with the system into two types: (1) *Actions* and (2) *Operations*. Actions represent users' interaction with UrbanSim recorded as messages in the UrbanSim log files. UrbanSim permits 43 different actions related to acquiring information in the COIN scenario. Example actions include view Intel reports and study trends (graphs). Operations are commands assigned to the units to perform on a region or individual. UrbanSim has repertoire of 21 different counterinsurgency operations that apply to an area of operation (AO). Example operations include patrol neighborhood, cordon and search, and host meetings with specific individuals.

The Hierarchical Task Model in UrbanSim

Figure 3 illustrates the hierarchical task model we have created for the UrbanSim counterinsurgency game. At the lowest level, subtasks related to information acquisition, solution construction, and solution assessment are linked to users' observable behaviors (actions and operations) in UrbanSim. Information seeking and acquisition involves understanding mission goals, identifying, evaluating the relevance of, and interpreting information to make logical decisions in the context of the overall mission goal and the current task. Solution construction and refinement tasks involve applying information gained to devise the solution approach (e.g., changing the actions in the sync matrix). Finally, solution assessment tasks involve interpreting the results of metrics provided by the system, such as the PS, LOE, PMESII, and CS values, to analyze, and if necessary, refine the solution approach.

The task model structure with accompanying computational algorithms are used to infer the users' generic cognitive skills. Similarly, we measure the users' proficiency on domain specific cognitive skills, i.e., their understating of clear (C), hold (H) and build (B) based on the operations selected by the user for their last few turns in the game. In order to measure the C, H, and B values for each turn, the regions in the AO are classified as clear, hold or build based on their corresponding Political and Military values. We adopted the classification of clear, hold, and build operations from (Vogt, 2012, p. 50) and also by consulting our domain experts in the ROTC program at Vanderbilt University. At every turn, we check to see if the clear, hold, and build operations are conducted in appropriate regions, and use this analysis to compute the users' proficiency in C, H and B.

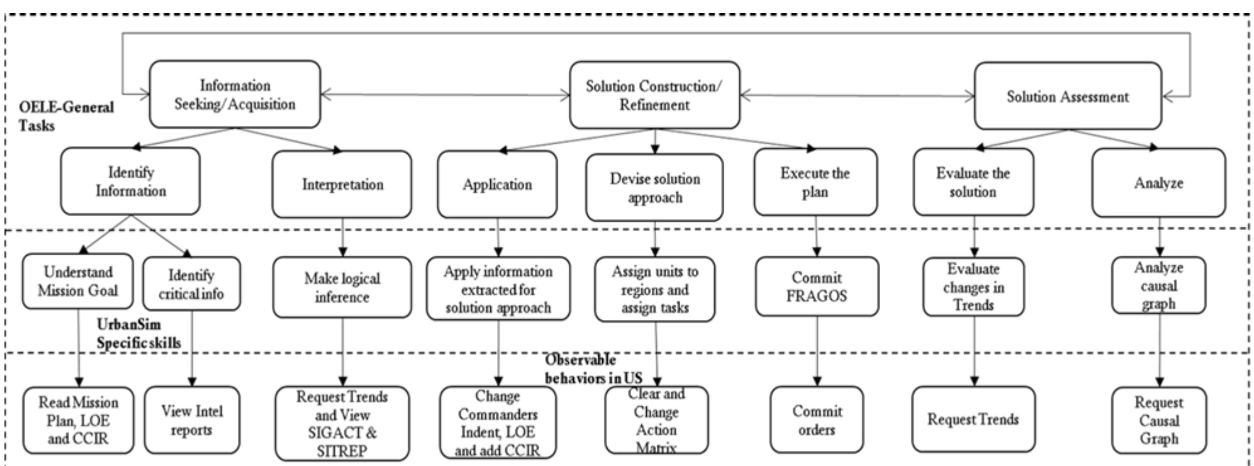

Figure 3. UrbanSim Hierarchical Task Model

Problem-Solving Strategies in UrbanSim

The goal of the UrbanSim learning environment is to help users understand the complexity of Counterinsurgency (COIN) operations, and apply strategies and decision-making skills to overcome these complexities. Successful application of the CHB strategy in complex counterinsurgency environments requires the trainee officer to develop and apply a number of additional strategies. In our work, we have identified three such strategies.

1) ***Situational awareness (SA)***: ability to identify and interpret key information in the Area of operations (AO) and develop a common operating picture (COP). This requires performing mission analysis as described in (McAlinden, et al., 2008).
2) ***Trade-off analysis (TA)***: a methodology for choosing operations taking into account the limited resources available, such as CERP funds, and units to conduct operations. Typically trade-off analysis may involve prioritizing operations to be conducted in different regions of the AO and then selecting and performing the high priority operations, while setting aside lower priority ones**.**
3) ***Second and third order effects (SOE)***: analyzing and predicting the effects of operations that are compatible with a prescribed end goal. An important consideration here is the decision to conduct lethal versus non-lethal actions realizing the direct and indirect effects that each of these operations may have on future CHB operations. Analyzing second and third order effects contributes significantly to both mission planning and evaluation.

In order to solve a complex task, it is clear that these strategies cannot be applied independently. For example, the user may first apply SA to generate a COP that takes into account the different regions, their military, political, and economic status, as well as the actors of significance in the current COP. A more complete understanding of the COP helps the user select appropriate COIN operations using the CHB strategy. However, given the limited number of personnel and budget available, the user has to determine a number of relevant operations that could be enacted, but perform tradeoff analysis between possible courses of actions to pick ones that best match the commander's intent (increase LOE values) and contribute to the overall goal, i.e., PS. The effects of the operations selected are provided as performance feedback and trend analysis to the user. In addition, after a few turns they may also review the effects of past operations to study second and third order effects, which can govern the selection of future operations.

GIFT User Model for UrbanSim

In order to analyze the users' proficiency on COIN operations in UrbanSim, we first analyze the Brigade commander's intent provided to the user at the start of the game. For example, this analysis provided the key goals to pursue in the Alhamra-2 scenario (a fictional Iraqi city, based very loosely on the conditions seen in the northern Iraqi city of Tal Afar): (1) stop influx of insurgents into the area of operations (AO), (2) improve effectiveness of utilities, such as, water, electric, trash depot and sewage plant, (3) ensure that the Iraqi security force (ISF) have local, reliable leadership, and is adequately funded and trained, and (4) build the regions' infrastructure to achieve economic viability. The performance on these key tasks are measured using performance measures Users' performance on these key metrics are extracted from UrbanSim log file.

We implemented GIFT user model for UrbanSim to measure the user's performance on cognitive skills, problem solving strategies, and metacognitive processes for each turn. For lack of space, we do not discuss the assessment of all problem-solving strategies in this paper. Instead, we discuss the algorithms for measuring users' Situation Awareness and Tradeoff Analysis strategies.

Tradeoff Analysis and Situational Awareness

Tradeoff Analysis measures the users' decision-making proficiency in choosing current operations, taking into account the limited amount of funds and personnel that are available to them. Tradeoff analysis focuses on the user's ability to choose operations that create a balance between performance measures, such as Effectiveness, Military Power, Capacity, and Coalition Support. Therefore, given the limited resources, trade-off analysis may involve prioritizing operations to be conducted in regions, and then performing the operations that maintain priority and balance. We have developed an algorithm (Algorithm 1) that uses information from the UrbanSim log data to compute the user's competence in TA. The first step of the algorithm classifies the AO regions as clear, hold or build using their corresponding Political and Military values. Overall the AO is categorized to be in a particular phase (C, H, or B) if the number of regions in that category exceed that of the other two. The TA measure for a user is then incremented if the actions and operations performed lead to an increase of the corresponding metrics as shown in Algorithm 1.

```
Algorithm 1: To measure User's Proficiency on Tradeoff Analysis
Input: Turn number, MP of Insurgent and Iraqi force, CP of Infrastructure, EF of utilities, CS, and PMESII
Output: User Proficiency on TA

For each Turn
1.   For number of regions, do
        Classify the region as Clear , Hold or Build Phase by its P and M values
   end
2. If Number of Regions in Hold Phase > Regions in Clear Phase  and Regions in Build Phase
            if Delta of CS > 0 and Delta of EF > 0
                      Increment TA competence by 0.1
            else   Decrement TA competence by 0.1
   If Number of Regions in Build  Phase > Regions in Clear Phase and Regions in Hold Phase
            if Delta of CP  >  0 and Delta MP(Police) > 0 and Delta of CS > 0
                      Increment TA competence by 0.1
            else  Decrement TA competence by 0.1
  end
```

Algorithm 1: To measure users' competence on Tradeoff Analysis in UrbanSim environment.

In general, if a user only selects operations that improve one or the other, then their ability to perform tradeoff analysis must be low. For example, if user performs operations that improve the values of capacity of infrastructure, military power of Iraqi security force and coalition support, then the user demonstrates good TA strategies.

Situational awareness (SA) measures the users' ability to identify and interpret key information in the area of operation (AO). In order to measure users' competence in SA, we analyze their performance in meeting the brigade commander's intent using performance measures, for example, the Coalition Support (CS), and Effectiveness (EF) of utilities. A sample of our algorithm to measure users' proficiency in SA during Hold phase is given in Algorithm 2. If we detect that the trend of any performance measure is negative, we consider the user's SA performance is low, hence, we further analyze the users' awareness of the environment in which they are operating. To understand the environment, the user needs to perform actions, such as read the mission statement, and understand the political, economic and military network of individuals and groups in the AO. We operationalize these actions as subtasks as described in the task model, Figure 3. List of subtasks required for SA are Identify, Interpret, Apply and Devise Solution. We check, whether the user has done these subtasks and then performed operations to improve the performance. If the user has performed these subtasks and trend of any performance measure is negative then we trigger a conversation with the user to further probe their awareness. Based on users' response in the conversation tree the competence of SA is updated.

```
Algorithm 2: To measure user's proficiency on Situational Awareness
Input: MP of Insurgent and Iraqi force, CP of Infrastructure, EF of utilities, CS, and PMESII
Output: User proficiency on SA values
Initial SA competence = 0.0
For each Turn
1.   For  number of regions, do
          Classify the region as Clear , Hold or Build Phase by its P and M values
     end
2. If Number of Regions in Hold Phase > Regions in Clear Phase and Regions in Build Phase
      If Delta of CS > 0 and Delta of EF > 0
                  Increment SA competence by 0.1
      else
      If  Average of Tasks(Identify, Interpret, Apply and Devise Solution) > 0.3
                 Start Conversation to user to check coherence between their action and operation.
                 Update SA competence based on user's response.
      else
end
```

Algorithm 2: Snippet of algorithm to measure users' competence on Situational Awareness

RESULTS

We validated the user model by correlating users' proficiency on problem solving strategies with their performance in domain-specific task.

Participants: Fourteen senior ROTC students at Vanderbilt University participated in our study. These students worked in pairs during two separate 2-hour sessions (approximately one month apart). Due to absences, these 14 students made up eight different groups over the two sessions, with four groups remaining the same for both sessions.

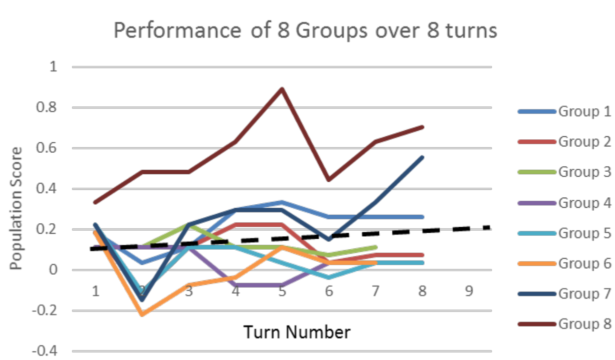

Figure 5: User performance on Population support for 8 turns

Procedure: Students used UrbanSim to practice and apply their knowledge of COIN principles in two scenarios: Al-Hamra and Al-Hamra 2. The study contains following steps (1) pre-test to assess user's under-standing of COIN principles and operations, (2) Students worked on the Al-Hamra 2 scenario for approximately 90 minutes, (3) After a break of about four weeks, students worked on the Al-Hamra scenario for approximately 90 minutes followed by (4) post-test. In both sessions, the course instructor led a debriefing discussion with the students after they had worked on the two scenarios. Students' interaction with learning environment and their discussions during the study are recorded using the Camtasia software.

Analysis: First, we analyzed the performance of all groups on population support for 8 turns as shown in Figure 5. Based on their performance, we separated the groups into high and low performers, as indicated by the dotted line in Figure 5. Then we selected one group from each category for detailed analysis. Figure 6, shows, for two groups, the high performing (group 7) and the low performing (group 2), their proficiency on strategies, population score and how they evolved as they interacted with the system for 13 turns. In Figure 6, the users' proficiency on SA of both groups is computed. At this stage they look to be about the same, however, group 2 was not able to maintain this proficiency level on their TA.

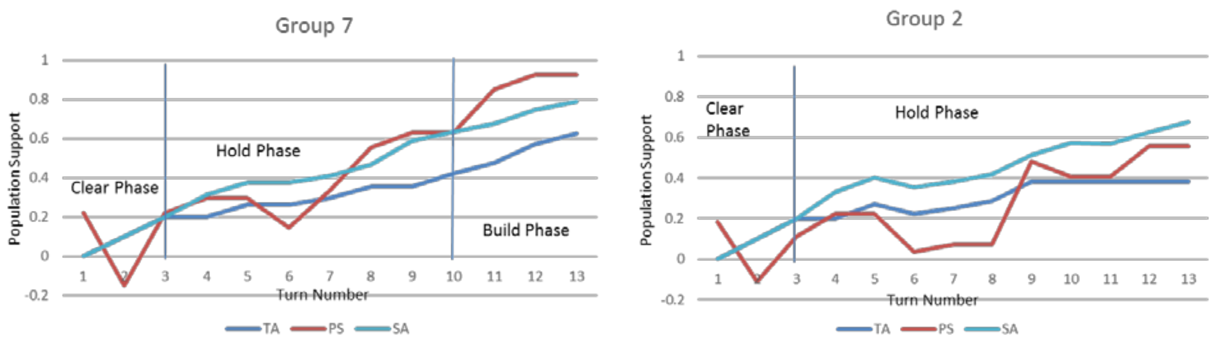

Figure 6. Two User Groups Proficiency on Tradeoff Analysis, Situational Awareness and Population Support

In the Clear phase, both groups chose operations to clear regions, and balanced use of resources. Therefore, their TA proficiency is increasing for every turn. In the Hold phase, group 7, chose operations that balanced Effectiveness of utilities versus Coalition support, hence their performance on population support (PS). Their choice of balanced operations is indicated by improved TA performance in the Hold and Build phases. As a result, they made smooth transitions from the Clear to the Hold to the Build phase. On the other hand, Group 2 did not choose operations that balanced Effectiveness versus Coalition support in the hold phase, hence their performance deteriorated and they could not make the transition from the Hold to the Build phase.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

In this research work, we proposed and implemented a user model using GIFT to measure the users' proficiency on cognitive skills and problem solving strategies, which can be used across different learning environments. Moreover, from our analysis we developed an instructional strategy algorithm to provide feedback to users based on their proficiency on cognitive skills and problem-solving strategies. In future, we propose to develop algorithms to measure the users' proficiency on metacognitive processes by analyzing the proficiency and trend values of cognitive skills, problem solving strategies and their performance in the domain-specific task and conduct research study to validate our proposed user model. Inferring metacognitive processes is a challenging task, since it happens in the users mind. Therefore, we are developing a combination of detection and querying methods to infer users' metacognitive processes online as they work on the system.

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