Adaptive Narrative Game for Personalized Learning

Y. Tang[a,b], *Senior Member, IEEE* and R. Hare[a], *Member, IEEE*

[a]Department of Electrical and Computer Engineering, Rowan University, Glassboro, NJ, 08028, USA.
[b]Institute of Smart Education, Qingdao Academy of Intelligent Industries, Qingdao, China.

***Abstract*—In recent years, engineering educators have begun to focus more on new learning methods that allow students to better understand and practice their subject matter. However, these approaches are not ideal for every student, and can be costly or time consuming to educators and institutions. Instead, a more individualized approach to learning is needed. This paper addresses this challenge through a narrative game system. Building on top of a previously created narrative game, the system utilizes metacognitive strategies (Roadmap, What I Know-What I Want to Know-What I Have Solved, and Think-Aloud-Share-Solve) and a random forest machine learning model to model a student's learning process. Based on data collected from the student, including emotional state, time, and errors in solutions, the system can estimate the current stage in the learning process. The student can then be offered prompts or hints to guide learning in a positive and productive direction, dynamically correcting misconceptions and allowing the student to learn at his/her own pace in a stress-free environment.**

***Index Terms*—Personalized Learning, Problem Based Learning, Narrative Game**

I. Introduction

Recent advancements in student education have begun to focus more on students' difficulties in reasoning, applying their knowledge to solve complex problems, and transferring that knowledge into new situations [1]. A problem-based learning (PBL) approach to addressing these issues has been gaining traction in the past few years [2]. Problem-based learning is a method of empowering students to conduct their own research and investigations while applying their knowledge and skills to solve defined problems [2]. However, PBL methods can pose challenges to students who prefer a more structured approach to learning. PBL approaches can even be frustrating if implemented improperly, or if the student lacks prior knowledge or motivation. As such, force-fitting students into a singular PBL model does not effectively serve the needs of all students [3].

Prior research indicates that many students benefit from a guided learning experience. Other students, however, prefer a more discovery-focused approach to learning [4], [5]. Several studies have shown the effectiveness of PBL in engineering education [5]–[7], but little has been done to attempt a more personalized approach to PBL [29], [30], with a system tailored to each student's individual learning methods. In fact, this lack of personalized learning in engineering education is such a critical unmet need that the National Academy of Engineering has listed it as one of its 14 Grand Challenges for Engineering in the 21st century [28].

Intelligent Tutoring Systems (ITS) have often been proposed as a solution to this issue [9], but these efforts usually lean toward direct support for the students, where students can request hints as needed. However, low-performing students often lack comprehension of the topic to the point where they cannot even ask proper questions. A proper ITS system with PBL features has yet to be constructed [31].

In contrast to ITS, narrative games also offer the potential use as a learning environment. These types of games often combine simulations of real-world phenomena with motivational and goal-based features. When attempting to learn new topics, students learn most effectively when they are actively involved in the cognitive process of problem solving, and when they receive feedback on how to improve as they learn. An expansive body of empirical work has provided strong evidence as to the benefits of narrative games in assessing [10]–[12] and supporting student cognitive development [13]–[18].

By integrating an ITS system within a narrative game, a personalized PBL approach to learning can be realized, which is the ultimate goal of this paper. In particular, an existing game system is transformed into a Personalized Instruction and Need-aware Gaming (PING) system. The existing game system [8], [17] utilizes three metacognitive strategies to enhance student learning; Roadmap, What I Know-What I Want to Know-What I Have Solved (KWS), and Think-Aloud-Share-Solve (TA2S). On top of these strategies, the PING system incorporates a multi-component probing feature informed by Social Cognitive Learning Theory [19] to obtain progress data from students, including their emotional states, specific subjects of difficulty, and time to completion [20]. By feeding the data obtained by the probes into a random forest machine learning model, a student's progress through the game can be tracked and their probable learning path is estimated. Based on this estimation, areas of learning difficulty can be identified and resolved with hints, prompts, or other learning guides.

The rest of the paper is organized as follows. Section II discusses an existing game system that will be used to build up the PING system. Section III discusses an overview of the PING system, with detail provided on the internal components, followed by the conclusion in Section IV.

This work was supported in part by the National Science Foundation Grant #1913809 and #1610164.

978-1-7281-2853-5/19/$31.00©2019 IEEE

II. Existing Game System

The existing game system, called Gridlock, features a character named Jack who witnesses a traffic accident at a major intersection of a town and then invites students to assist him in redesigning the traffic light controller. The traffic light controller is a typical sequential machine, often used as an instructional example in digital logic design.

To activate a student's prior knowledge, the KWS training is implemented through a series of questions related to the problem-solving stages presented in the game as exemplified in Fig. 1. According to the student's responses, the student is directed to different sections of the roadmap as shown in Fig. 2 for the study materials that they definitely need to move on with the design. TA2S training is implemented in the game through the use of a chat server. This allows students to interact with each other as they progress through the game, producing social stimulation and intellectual synergy.

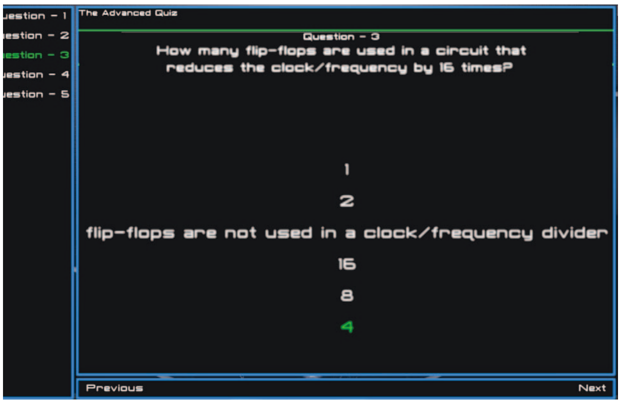

Fig. 1. Example question prompt within the game, asking the player a basic question about digital logic design (text enlarged for readability).

Once the student has progressed through the training methodology, they are given an in-game tool to assist them with their designs. Once they have made a design, students are directed to finalize their traffic light design in the Verilog hardware description language. The game system then invokes ModelSim-Altera Starter to validate the design. As the students go through this process, the game server logs all student actions, providing abundant data with which to analyze student performance and game effectiveness. This data collection is a crucial element in building and refining the PING system.

Gridlock is a good starting point for developing the PING system as it has previously been evaluated as a learning tool in seven courses with over 300 students at both Rowan University and Tennessee State University. In previous testing, pre and post-tests on student content knowledge were given to both control groups and groups that played Gridlock (treatment groups) [18]. The results of these tests are shown in Fig. 3. Both sections that incorporated the game showed significant improvement in their knowledge of sequential circuit design when compared to sections that did not incorporate the game. In post-game surveys, students described the game system as more engaging and interesting than conventional problem

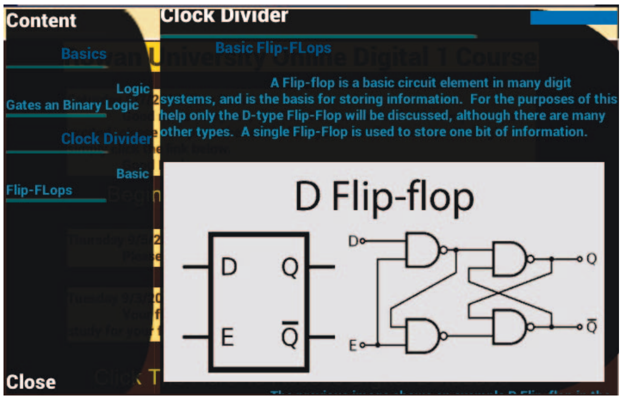

Fig. 2. Example of instructional content within the game. In this case, this prompt is shown to a student who answered incorrectly on a question regarding this content

solving with paper and pencil, and also said that it increased their interests in their major.

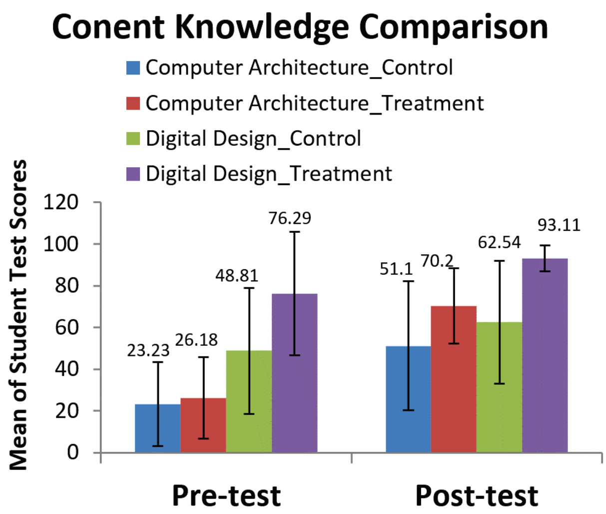

Fig. 3. Comparison of content knowledge. Group difference significant (t test $p<0.05$) [18]

While effective for some students, other students felt that the guidance in game could be more detailed with additional coaching. Thus, the game still has room for improvement and modification. If the game system is better able to extract information about learning differences from each student and provide appropriate customized support, the resulting system will be more effective and efficient. Therefor, it is necessary to transform the existing game, Gridlock, into a PING system and to investigate the extent to which such a personalized system will improve students' problem-solving skills.

III. Personalized Instruction and Need-aware Gaming (PING) System

A. PING System Overview

At its core, the main benefit of the PING system is the ability to predict both a student's level of domain knowledge as well as their learning path. Utilizing these predictions, personalized learning support can be provided to the student in the PBL game environment. However, the data needed for this personalized learning is based on the student, and is only available through observation of that student's learning process. Therefore, any attempt to develop a practical personalized learning solution must involve a decision-making process that can handle rich data streams communicated by the game system, extract pertinent knowledge about a student's state or needs in their learning process, and exploit the acquired knowledge for personalized learning. The implementation of PING can be represented by a closed-loop control system as shown in Fig. 4.

When comparing automated systems to human tutors, the latter often proves significantly more effective. Human tutors can easily gauge the required level of guidance a student needs to keep them learning productively. PING attempts to mimic the effectiveness of human tutors by estimating a student's current knowledge and providing support based on that. By integrating the four main components of the PING system on top of the existing metacognitive strategies present in the game, the system's ability to estimate a student's learning progress and provide support is greatly increased, leading to an effective learning environment.

The Student Comprehension Model (SCM) is the central decision-making component of the PING system. This model features a machine learning based system to analyze student responses and provide a prediction on whether the student has achieved a positive trend in their learning of the topic. Using the prediction, proper learning support for that student is established through hints, prompts, and cues to assist that student in their learning process. This prediction and the learning support are provided by a decision tree based machine learning algorithm which has been designed and trained to model a mapping between the causes (e.g., a student's knowledge of a concept) and effects (e.g., the student being offered specific learning support) in a student's learning process.

To gather the required data for the SCM, Social-Cognitive-Theory-based probing collects process variables for the extraction of pertinent knowledge about a student's perception of the task and task variables, specific needs and limitations, and capacity to generate routines of activities for problem-solving. The Student Knowledge Database logs the events and records the student's usage of the game system, including their mouse movements, emotional signs, exploration of the KWS system, responses to questions, and use of chatting functions.

The Instruction Database is a collection of hints, prompts, and cues which have been organized according to milestones and stepwise challenges in the student's learning path

B. Integrating Social-Cognitive-Theory-Based Supports into Game Interactions

To address the specific needs or difficulties of students and to improve the instructional practices of the game, the integration of student learning supports into the gaming environment is a necessity. These student learning supports are grounded in Social Cognitive Learning Theory (SCLT) and implement evidence-based practices from traditional instruction in the digital gaming environment [19]. SCLT emphasizes the social aspect of learning, which is best supported with an instructor who can scaffold their lessons to guide the learner to new cognitive understanding. SCLT also theorizes that learning takes place when learners are most involved and engaged with tasks that interest them.

While research has shown the benefits of teacher probing and scaffolding on student learning, current educational gaming environments often lose these benefits as the students mostly interact independently with the gaming system [22]. In addition, students who struggle with content in the game often have difficulty finding their next steps when correcting misunderstandings and progressing in the game. To truly engage a student and replicate a classroom learning environment, the student needs both feedback about what they did wrong and multiple opportunities to learn a concept or topic [23]. Without appropriate learning support, students may not utilize effective learning and problem solving strategies.

By utilizing a learning theory based instructional model with four components (probes, time, errors, and emotion), students' learning can be properly evaluated and individual support can be provided to address errors and misunderstandings in the PBL game environment. The four components are described in more detail below. The model utilizes information on known and common errors in student understanding to estimate either what the student needs to learn or what solution path the student is likely attempting to pursue. Based on these estimates, each student can receive useful, customized learning support.

To implement probes in the PING system, students are prompted from a pool of questions that are designed to detect signs of learning difficulties. The prompts are pertinent to the problem solutions in the PBL gaming environment, containing information about knowledge, facts, or goals of the problem solving process. These prompts are meant to engage students in a manner similar to a traditional learning environment, making them think about solutions to problems they do not necessarily know how to answer. In the Gridlock game, a pop-up question might ask ”Which of the following best describes the problem in this game?” Such pop-up questions have proven themselves as effective instructional strategy in encouraging self-regulation and self-reflection, as well as directing students to important aspects of the problem [1]. To augment the prompt implementation and avoid the issue of students memorizing the answers to the questions, the questions are also picked randomly from a large selection.

Time is another significant indicator of learning difficulties for the PING system to measure. When a student takes an unusually long time to respond to a problem, it is a sign of time management issues or technical difficulty. In this case, a question prompt can be utilized to evaluate if the student lacks essential knowledge to solve the problem or if the student is simply distracted. An example of this from the Gridlock game is shown in Fig. 5. In this case, a student who has taken an extended amount of time constructing light switch logic

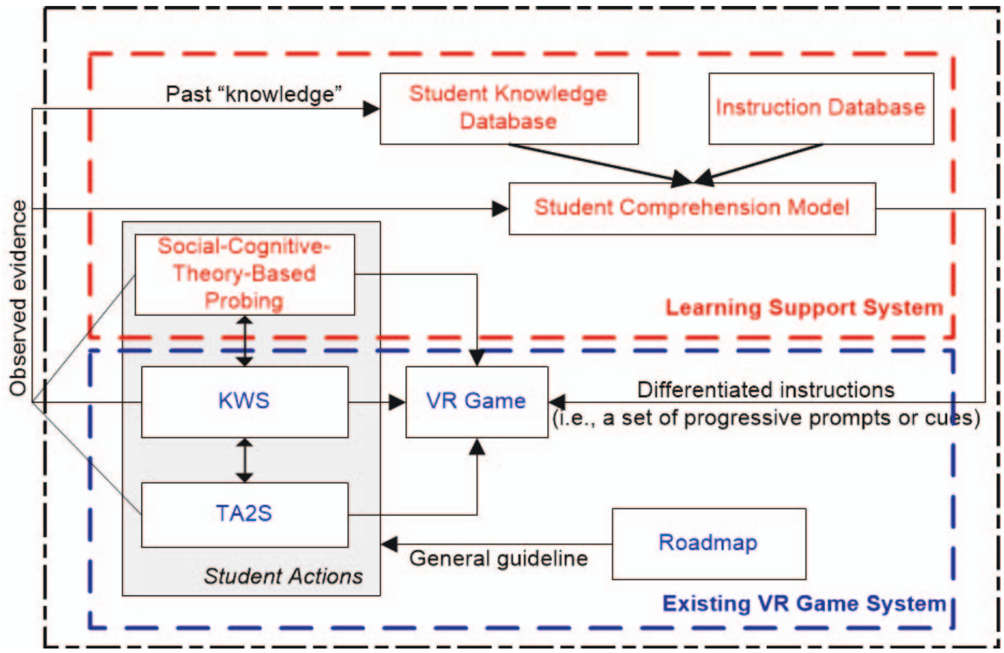

Fig. 4. Architecture of the PING system. Components enclosed in blue represent components already within the existing game system. Components in red represent the PING system components to be implemented in the game.

Fig. 5. In-game example of a time-related prompt. In this case, a student who has stopped progressing for some time is offered a question to refresh their knowledge (Text has been scaled up for readability).

would be prompted with a basic question about the early steps of solving the problem. If the response indicates a lack of essential knowledge, then the student can be directed to further help regarding the topic or an example video of an expert utilizing the same method to solve a problem.

The existing game system also provides the capability for error diagnosis of student designs. Fig. 7 shows the game identifying several issues with a submitted design. The PING system expands upon this error diagnosis to determine and categorize the nature of an error (e.g., problem misidentification or wrong syntax). It then offers personalized support for correction of that specific error. By providing feedback on student performance and allowing re-submission, the PING system allows students to self-regulate and learn by utilizing a task-performance feedback cycle.

Emotional indicators can often provide powerful indicators of positive or negative trends in learning, with certain emotions, such as confusion or frustration showing difficulties. The PING system utilizes a camera-based facial emotion recognition system to track fluctuations in the emotions of the student through facial expressions. This information can be forwarded to the SCM to provide instructional guidance appropriate to that student's emotions. For instance, confusion might indicate lack of critical information, while frustration might indicate lack of understanding of how to solve the problem. By recognizing a student's emotional state, timely and individualized feedback can be provided to the student. For instance, if a student seems confused, the system can provide indirect hints to restore cognitive equilibrium within the learner.

C. Student Comprehension Model (SCM)

The purpose of the SCM is to model a student's learning process through the use of observational data of the student's behaviors and emotions during the learning process. However, a great level of uncertainty comes from human-centric data, and more subtle patterns can be difficult to discern. With machine learning or pattern recognition, these subtler patterns in the human-centric data can be discerned and modelled by approximating a mapping function between a set of inputs (also called features) and one or more outputs (also called predictions).

Unlike human decision makers, machine learning-based approaches make objective decisions/predictions based on data and prior knowledge. In a rapidly growing field such as machine learning, a multitude of algorithms and approaches can be applied with each approach having its own advantages,

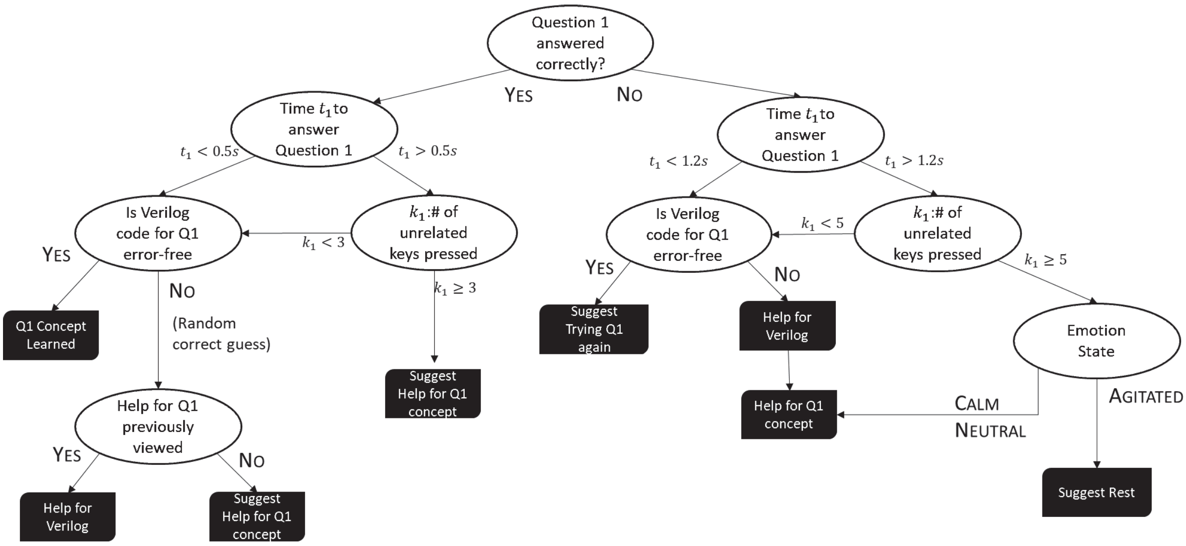

Fig. 6. A simplified example of one decision tree in the Student Comprehension Model [18]

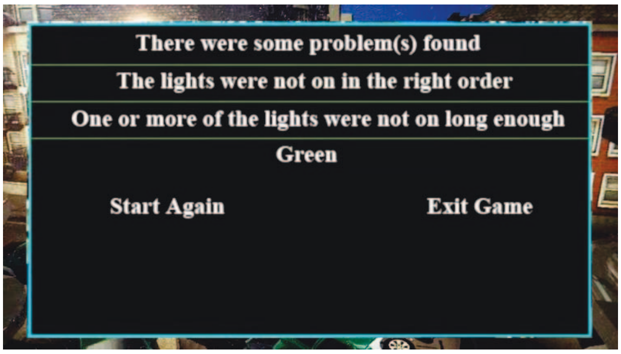

Fig. 7. In-game example of error checking; A student has submitted a design that did not meet the problem criteria, and the problems with the design are made clear to the student.

characteristics, and shortcomings. In the majority of these applications, choosing an appropriate algorithm (also called a classifier or model) for the task at hand is the most critical task. In the case of the SCM, a random forest approach [24], [25] was chosen due to its strong fit to the problem and many desirable properties, described below.

A random forest is an ensemble of decision trees. A decision tree is a graphical model that consists of a group of antecedents and consequences (basically if-then rules). The rules are organized in a hierarchical manner to make a final decision based on a series of questions. An example decision tree for this specific problem is shown in Fig. 6.

For this problem, decision trees hold several advantages over other existing machine learning models. They are not based on a similarity or distance measure, and they can naturally handle nominal (categorical), ordinal (ordered), and cardinal (numerical) data. Most classifiers cannot naturally handle nominal data such as the user data collected by the PING system. By using a decision tree, the data does not need to be transformed into ordinal or cardinal data. Furthermore, decision trees offer intuitive decisions that can easily be traced back to the specific feature values that led to that decision.

A random forest generates a set of many such trees, each trained on slightly different subsets of the training data. In concept, ensemble-based systems are very similar to real-life scenarios, relying on collective wisdom of multiple decision makers to arrive at a final decision. These ensemble-based random forests have been proven to be significantly more stable, resistant to errors, noise, and variations in the data [24], [25] compared to single tree-based models. The ensemble-based models have also shown significant performance improvements over single classifier-based approaches [26], [27].

The SCM is a key component of the PING system. It tracks the student's learning process while the student interacts with the game. Such a model also provides predictive estimates of a student's ability to solve problems. The SCM, then, is an aggregation of a student's problem solving skills skills into a hierarchy, where the nodes of the tree represent different actions that a student may take in the process of solving the problem. If the model has sufficient evidence that a student knows a specific fact, the model focuses on the antecedents of other nodes and branches in the tree. As the appropriate path of the tree is traversed based on the current evidence, the model renders a prediction associated with the appropriate action to take. This decision tree-based model enables the PING system to provide individualized coaching to maximize students' learning outcomes.

As previously stated, the four components of the data (probes, time, error, and emotion) are collected from students as they play the game. This data is represented by various measures such as previous visits to the tutorial modules of the game, unrelated key presses, facial expressions, and time to progress through sections of the game. If other features are identified during testing and studies of the PING system, they can and will easily be added into the overall process.

With previously obtained data that has already been hand-scored and annotated by a human expert, the decision tree ensemble was trained. With a random forest, the computational complexity is relatively low. As new training data is obtained from experimentation and testing of the game, the model can be rapidly updated, and the model will continuously improve. With larger amounts of data and increased reliability of data as testing and experimentation continues, the model will become more stable and the predictions of the tree will become more accurate.

IV. Conclusion

To introduce a more personalized approach to instruction in Engineering and Science, this paper proposes the Personalized Instruction and Need-aware Gaming system. By taking a problem-based learning approach to teaching and applying a machine learning-based random forest model that accurately predicts students' learning patterns, students can be offered individualized assistance that fits their specific learning pattern. This system appeals to both students who prefer guided learning and students who prefer discovery-based learning. Through this system, students will gain more experience in reasoning, applying their knowledge to solve complex problems, and transferring that knowledge into new situations. In doing so, these students will be better prepared for the rapidly changing and highly competitive environment they one day seek to enter.

References

[1] X. Ge, L. G. Planas and N. Er, "A Cognitive Support System to Scaffold Students Problem-based Learning in a Web-based Learning Environment;" The Interdisciplinary Journal of Problem-Based Learning, vol. 4, no. 1, pp. 30-56, 2010.

[2] J. R. Savery, "Overview of problem-based learning: Definitions and Distinctions," Interdisciplinary Journal of Problem-Based Learning, vol. 1, no. 1, pp. 9-20, 2006.

[3] APlus+, association of personalized learning services, https://theaplus.org/personalized-learning/.

[4] P. A. Kirschner, J. Sweller and R. E. Clark, "Why minimal guidance during instruction does not work: an analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching," Educational Psychologist, vol. 4, no. 2, pp. 75-86, 2006.

[5] J. Hattie, Visible Learning: A Synthesis of Over 800 Meta-Analyses Related to Achievement. New York: Routledge, 2009.

[6] A. Yadav, D. Subedi, M. A. Lundeberg and C. F. Bunting, "Problem-based Learning: Influence on Students' Learning in an Electrical Engineering Course," J. Eng. Educ., vol. 100, no. 2, pp. 253-280, 2011.

[7] R. Mayer. ,"How engineers learn: a study of problem-based learning in the engineering classroom and implications for course design," Dissertation, Iowa State University, 2013.

[8] Empowering Students with Engineering Literacy and Problem-solving through Interactive Virtual Reality Games, http://users.rowan.edu/ tang/VR_games/home.htm.

[9] Robert Sottilare, et al., Design Recommendations for Intelligent Tutoring Systems Vol. 3 Authoring Tools & Expert Modeling Techniques U.S Army Research Laboratory.

[10] D. Zapata-Rivera, "Adaptive, assessment-based educational games," in Intelligent Tutoring Systems, V. Aleven, J. Kay and J. Mostow, Eds. Springer, 2010, pp.435-437.

[11] Valerie J. Shute, et al., Measuring problem solving skills via stealth assessment in an engaging video game, Computer in Human Behavior, 63, 2016, pp. 106-117.

[12] V.J. Shute & S. Rahimi, Review of computer-based assessment for learning in elementary and secondary education, Journal of Computer Assisted Learning, 33, 2017, pp. 1-19.

[13] Ying Tang, Kauser Jahan, and Talbot Bielefeldt, The Effectiveness of An Adaptive Serious Game for Digital Logic Design, Proceedings of 2015 ASEE Annual Conference and Exposition, Seattle, Washington. 10.18260/p.24861.

[14] Y. Tang, S. Shetty and X. Chen, "Educational effectiveness of virtual reality games promoting metacognition and problem-solving," in 2012 ASEE Annual Conference, San Antonio, Texas, 2012, pp. 25.495.1-25.495.7.

[15] Ying Tang, Sachin Shetty, et al., Sustain City A Cyberinfrastructure-Enabled Game System for Science and Engineering Design, Journal of Computational Science Education, Vol. 3, No. 1, 2012, pp. 57-65.

[16] Christopher Franzwa, Ying Tang, Aaron Johnson*, and Talbot Bielefeldt, Balancing Fun and Learning in a Serious Game Design, International Journal of Game-Based Learning, 4(4), 37-57, Dec. 2014.

[17] CI-TEAM Demonstration: Interactive and Collaborative Learning Environment using Virtual Reality Games Promoting Metacognition for Science and Engineering Design in Context, http://sustaincity.rowan.edu/

[18] Ying Tang, et al., Sustain City Effective Serious Game Design in Promoting Science and Engineering Education, in Design, Motivation, and Frameworks in Game-Based Learning, IGI Global, 2017

[19] Zimmerman, B. J. (2013). Theories of self-regulated learning and academic achievement: An overview and analysis. In Self-regulated learning and academic achievement (pp. 10-45). Routledge.

[20] X. Ge, C. H. Chen, K. A. Davis, Scaffolding novice instructional designers problem-solving processes using question prompts in a web-based learning environment, Journal of Educational Computing Research, 33(2), 219-248.

[21] M. Oliveira and J. A. Serrano. Learning roadmap studio: new approaches and strategies for efficient learning and training processes, http://www.elearningeuropa.info/files/media/media16938.pdf.

[22] Chin, C. (2006). Classroom interaction in science: Teacher questioning and feedback to students responses. International journal of science education, 28(11), 1315-1346

[23] Kim, B., Park, H., & Baek, Y. (2009). Not just fun, but serious strategies: Using meta-cognitive strategies in game-based learning. Computers & Education, 52(4), 800-810.

[24] T. Hatie, R. Tibshirani, J. Friedman, The Elements of Statistical Learning, Data Mining, Inference, and Prediction, 2nd edition, pp. 587-624, Springer, 2009.

[25] G. Biau, Analysis of a Random Forest Model, Journal of Machine Learning Research 13 (2012) 1063-1095.

[26] Polikar R., Ensemble Learning, in Ensemble Machine Learning: Methods and Applications, Cha Zhang and Yunqian Ma, editors, Springer, 2012.

[27] Kuncheva L.I., Combining Pattern Classifiers: Methods and Algorithms, 2/e, John Wiley and Sons, 2014.

[28] National Grand Challenges, http://www.engineeringchallenges.org/challenges/learning.aspx

[29] Harvey Siy, et al. SPARCS: A Personalized Problem-based Learning Approach for Developing Successful Computer Science Learning Experiences in Middle School, Proceedings of 2017 IEEE International Conference on Electro Information Technology, EIT 2017, pp. 611-616.

[30] Brabazon, D., et al., Supporting Problem-based Learning in Moodle using Personalised, Context- specific Learning Episode Generation, Proceeding of 1st Moodle Research Conference, Heraklion, Crete, Greece, September 14-15, 2012.

[31] James C. Lester, et al., Serious Games Get Smart: Intelligent Game-Based Learning Environments, AI Magazine, Vol. 34, No. 4, 2013.