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Evaluation of a Game-Based Personalized Learning System

Mr. Ryan Hare, Rowan University

Ryan Hare received his B.S. in Electrical and Computer Engineering from Rowan University in 2019. He is currently pursuing his M.S. in Electrical and Computer Engineering at Rowan University. His current research focus is applying machine learning and games to enhance student education, particularly in STEM fields.

Dr. Ying Tang, Rowan University

Ying Tang received the B.S. and M.S. degrees from the Northeastern University, P. R. China, in 1996 and 1998, respectively, and Ph.D degree from New Jersey Institute of Technology, Newark, NJ, in 2001. She is currently a Professor of Electrical and Computer Engineering (ECE) at Rowan University, Glassboro, NJ. Her research interests include virtual reality and augmented reality, artificial intelligence, and modeling and scheduling of computer-integrated systems. Dr. Tang is very active in adapting and developing pedagogical methods and materials to enhance engineering education. Her most recent educational research includes the collaboration with Tennessee State University and local high schools to infuse cyberinfrastructure learning experience into the pre-engineering and technology-based classrooms, the collaboration with community colleges to develop interactive games in empowering students with engineering literacy and problem-solving, the integration of system-on-chip concepts across two year Engineering Science and four year ECE curricula, and the implementation of an educational innovation that demonstrates science and engineering principles using an aquarium. Her work has resulted in over 100 journal and conference papers and book chapters.

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Abstract

Modern classroom settings require integrating many students of varying backgrounds and varying levels of classroom performance into the same educational process. Ideally, each student should receive personalized support that is tailored to their specific learning style. However, with limited resources and time available to educators and teaching facilities, personalized support is often infeasible. To address this issue, this project focuses on a learning system that uses artificially intelligent agents to provide students with personalized feedback and support. To further engage students, the system is built on top of an existing narrative game environment called Gridlock. Gridlock provides students with a narrative game experience that focuses on creating a traffic light controller to teach students the basics of sequential digital logic design, a core component in both Computer Engineering and Computer Sciences. Gridlock was chosen as it already implements several meta-cognitive strategies designed to promote student learning and student self-reflection, thus giving a solid foundation to build the learning support system on top of.

This paper reports preliminary results from early testing and continued development of the Gridlock system. In testing the game system, students in Introduction to Digital Systems courses and Computer Architecture courses at Rowan University utilized the game as a supplementary tool to assist them with lab work. The overall goal of the improved game system is to improve student comprehension and classroom results. Additionally, the finished system is planned to be fully automated, requiring no intervention from instructors or researchers. Assessments of the effectiveness of the game system will be shown through the following:

1. Student game performance.
2. Student performance on content tests related to the game content.
3. Student lab work performance.
4. Student surveys.

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2. Introduction

Major research within higher education focuses on the divide between discovery-based student learning and directly-guided student learning [1],[2]. This is especially true within engineering and other STEM topics due to the complexity of the material. A large amount of both research and school curricula generally adopts a one-size-fits-all approach [3],[4]. While easily implemented and generally best for all students, a number of students are still left behind when their ideal learning approaches deviate largely from the standard. Further, some students can lack motivation or prior knowledge, negating any benefits that exploration-based learning might have for them.

Another recent trend within engineering education is a focus on problem-based learning (PBL) [5]. This approach engages students in a learning process through the use of one or several real-world problems, immersing students in a problem-solving process while still allowing them to explore and gain knowledge as they attempt to create a solution. Especially within engineering, PBL approaches have seen success [2],[6],[7], though they still have issues if students prefer more structured, guided learning.

Intelligent Tutoring Systems (ITS) [8] are one such approach to addressing these issues. These systems often provide a basic level of student guidance and an exploration-based learning process, however they often lack methods or content that engages students within said learning process. Such systems also often require instructor intervention or configuration, using up highly-limited instructor time and resources. A logical step, then, is creating an ITS within a PBL setting, thus achieving the best of both worlds: An ITS that provides guidance to students who prefer structured learning; and a PBL environment to students who prefer discovery learning.

To truly immerse students in PBL, they need a problem and an environment that provides both a space to explore and real-world context for the problem. One such environment for this purpose is narrative, virtual game environments. Serious games (SGs) [9] can provide educator benefits in terms of student assessment [10],[11],[12] and can provide self-contained student support [13],[14],[15],[16],[17],[18]. Further, a fully automated system built on top of a game could provide students with an educational experience without instructor intervention, freeing up instructor time and resources.

The proposed personalized learning system implements a guidance-focused ITS on top of a narrative game that immerses students in a PBL process. The narrative game, known as Gridlock [19],[17], is a domain-specific game that educates students in the basics of sequential logic design. The fully completed system is be referred to as the Personalized Instruction and Need-aware Gaming (PING) system. The goal of the system is to monitor student progress as they play and adjust both their path through the game and the information and assistance they receive. This timely support occurs as students are immersed in the problem-solving process, and seeks to address learning difficulties as they arise. The end result should be improvements in student classroom performance, domain knowledge, and problem-solving skills. The PING system also aims to be fully automated, requiring little (if any) instructor interaction. And while some technical personnel will initially be required for resolving issues that occur during early testing, the game system should eventually operate for a number of years without further development.

To make informed decisions about what assistance to provide to the student, the system gathers student information using probing methods based on Social Cognitive Learning Theory (SCLT) [20]. The PING system then makes use of artificially intelligent reinforcement learning agents to iteratively learn the best decisions to make at any point based on the information gathered by the probing methods. Finally, a colored Petri net model [21] allows for the modeling of student movement through the game, tracking the student and selecting the best paths and decisions at any decision point.

Section 3 provides an overview of Gridlock and the learning supports integrated within the game. Section 4 provides a brief summary of the components of the PING system and the intelligent student assistance. Section 5 provides results of case studies run with the Gridlock game including student performance comparisons, student surveys, and simulated results for unimplemented systems. Finally, section 6 offers conclusions and future directions for this project.

3. Gridlock Game System

Gridlock is a virtual learning environment that places students within a city known as Sustain City. Within this city, students witness a traffic accident due to a failed traffic light and are tasked with rebuilding the traffic light controller. This controller is a common lab project for students in courses related to Digital Logic Design, and provides students with a good overview of the basic necessities of these types of digital logic devices. Gridlock is designed to be run in related courses in conjunction with a lab assignment with the game augmenting the lab experience.

When students first enter the game, they are quizzed to establish a benchmark of their knowledge. As they move further through the game, they visit various stations that test them on concepts related to the overarching goal; for example, one station covers the syntax of Verilog code, the coding language required by the lab to create the solution. These stations contain study guides, videos, examples, and other materials to aid student learning. At the end of each station, students are quizzed on the material. Whenever a student enters one of these stations, the reinforcement learning system selects which assistance to provide. In this way, students are provided with different materials and comments based on their performance. Further, when a student exits a station, they are tested on the material. If the student then demonstrates that they still lack knowledge on the given material, they re-enter the station and are provided with different material to review to further enhance their learning.

Student assistance is determined through student feature vectors that are constantly gathered and updated. These vectors provide a numerical indicator of student performance as related to each of the areas of knowledge related to solving the overarching problem. Within Gridlock, student feature vectors are gathered and updated through quizzes. These vectors then allow the reinforcement learning system to make informed decisions about which help to provide to students. Gridlock currently tracks the following values:

- Total quiz score
- Completion times
- Student’s confidence in their answer as a self-reflection metric
- Indices of questions students are shown
- Number of key presses and total mouse movement to track frustration or boredom
- Emotion values recorded through webcam

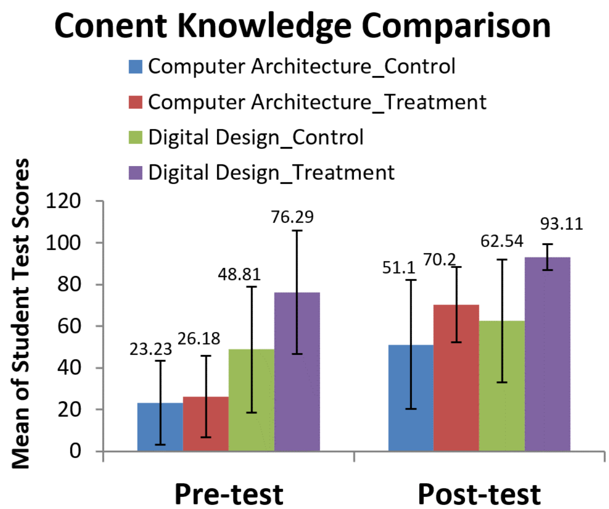

Figure 1: Comparison of content knowledge. Group difference significant (t test $p<0.05$) [Tang *et al. , 2017].*

Even before integrating the PING system with Gridlock, the game was designed with meta-cognitive strategies in mind to augment student learning. First, Know-Want to know-Solve (KWS) prompts students to write records of the material that they have already learned and the material they still need to learn to solve the problem. Second, Think-Aloud-Share-Solve (TA2S) encourages students to cooperate and discuss problems and solutions with each other to enhance the learning process. Finally, Roadmap gives students a guideline of the knowledge that they both have already learned and are going to learn. This gives students an idea of where they stand within the learning process [22].

Previous testing has shown that the lab assignment augmented with Gridlock is a good learning tool [18]. As shown in Figure 1, students who used Gridlock in conjunction with the lab assignment had better and more consistent post-test performance after doing the lab assignment when compared to those who performed the standard lab. Through testing over 300 students in 7 courses, students overall deemed the game more engaging when compared to a standard lab experience [18].

4. PING Architecture

The complete implementation of the PING system is designed to operate without any intervention from researchers or instructors. With this implementation, it requires significantly less time and resources to implement in a classroom setting, giving the system an edge over other ITSs and over human tutors. Further, the goal of the PING system is to achieve a similar level of learning support to human tutors through the personalized approach and the intelligent decision-making.

Figure 2 shows an overarching view of the entire system. As shown, the system observes student actions as they interact with the game and the meta-cognitive systems. The system then uses the instruction database and the comprehension model to provide personalized prompts and select

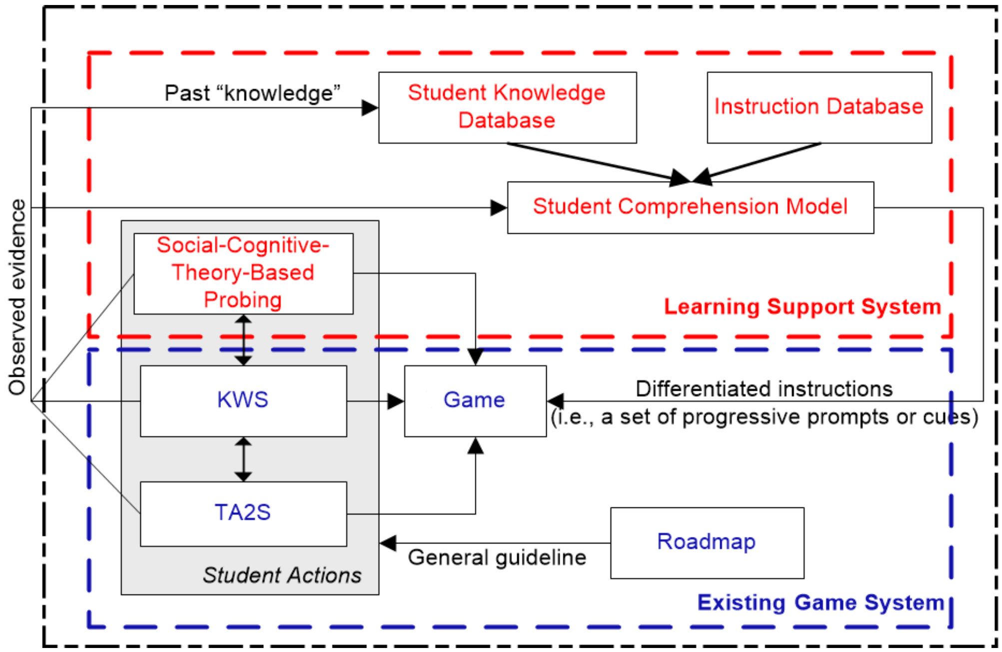

Figure 2: PING System Architecture. Components in blue exist within Gridlock. Components in red are the additions made by adding the PING system. [23]

different content based on a student's performance.

4. Student Knowledge Database

The Student Knowledge Database is the center for storing student feature vectors. Within it, one vector is stored and updated as appropriate for each content-specific section in the game. Within Gridlock, there are 7 of these sections. The database also contains a metric for grading student performance based on these feature vectors. In some cases, using these grades instead of the entire data set allows the reinforcement learning agents to learn quicker and make better decisions overall.

4. SCT-Based Probing

As stated, student feature vectors are gathered and updated by the SCT-Based probing system within Gridlock. This system observes student behavior as they solve problems and answer quiz questions to determine their level of knowledge. Basic data, such as quiz scores and completion times are gathered, along with more complicated metrics. For example, with each question and problem, students are asked to self-reflect on their performance and rate how confident they are in their answer. An incorrect answer with a high confidence could suggest that the student needs a large amount of help, while a correct answer with a low confidence could suggest guessing, or that more review is required.

The system also keeps track of the questions given to students so that informed decisions can be made about the exact areas of difficulty students have. Further, the student's level of boredom or frustration is also estimated by the system by measuring key presses and mouse movements and comparing them to an average. If students are overly active in these movements, it may indicate that they grow bored or frustrated with the content and would benefit from a break or a change in pace.

Finally, the probing also focuses on interpreting student emotions. As many students in today's learning landscape make use of personal computers for their learning, integrated webcams are often freely available for use by the system. By capturing images of students as they complete tasks and answer questions, the system can estimate student emotions and take these into account when personalizing a student's learning experience. In the case of Gridlock, this emotion detection adapts a method from Bahreini, van der Vegt, and Westera [24] to rank images with seven different emotions (happy, sad, surprised, afraid, disgusted, angry, and neutral).

4. Student Comprehension Model

The Student Comprehension Model (SCM) has two components that work in tandem to model and control student movement through the game. The first component of the SCM is a colored Petri net model. This net is a directionally-connected set of nodes where markers representing students can flow through the system. This gives the system constant knowledge of both where the student is in the game and where the student can go from their current position. Further, the artificially intelligent reinforcement learning agents can control the flow of markers through this network, modifying situations or paths in the game and controlling both where the student goes and what content they interact with.

The second component of the SCM is the reinforcement learning agents that are used for decision-making. The agents use the student's data to make informed decisions about where the student should go next and what help to provide to the student. In turn, once the student has taken that path or absorbed that content, the agent receives a numerical reward based on the student's improvement (or decline), as well as an observation of the effect that action had on the student's performance. As more students play the game, the agent iteratively learns how to maximize the reward received, choosing the best action for any given student. Figure 3 shows a top-level diagram of how the reinforcement learning agents iteratively learn.

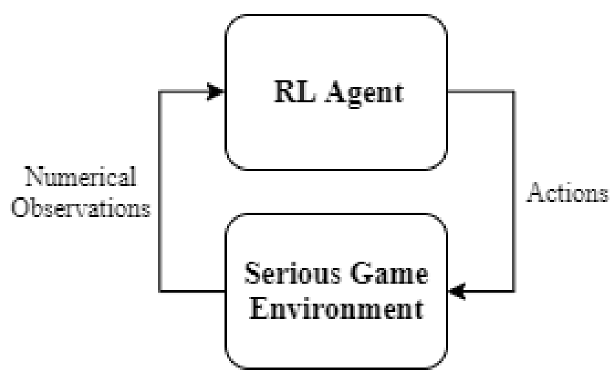

Figure 3: Top-level diagram showing the iterative way that reinforcement learning agents learn to maximize their rewards.

As an example of the decisions made by the system, a selection of student data from pilot tests of Gridlock was taken and sent through a simulated version of the system. Table 1 shows an example from one of the tests of the path the system takes the student through depending on their initial performance in each section. In this case, students were graded on a scale from 0 to 2, with 2 being mastery of the subject material. As shown, the system ignores sections that the student has already shown mastery of and instead focuses on areas that the student has difficulty with. First, it enters section 1 and 7, allowing the student to fully master material they had slight issues with. Then it went to the material where the student had deeper issues, eventually ending the game once the student had mastered all 7 sections.

Step	Grade for Each Section	Section Decision
1	1, 2, 2, 0, 0, 0, 1	1
2	**2**, 2, 2, 0, 0, 0, 1	7
3	2, 2, 2, 0, 0, 0, **2**	5
4	2, 2, 2, 0, **2**, 0, 2	6
5	2, 2, 2, 0, 2, **2**, 2	4
6	2, 2, 2, **2**, 2, 2, 2	End

Table 1: Example path chosen by the reinforcement learning system with the student's grade for each section.

5. System Evaluation

Among testing in relevant courses at both Rowan University and Mercy College, students were tasked with completing the related lab assignment both with and without the use of the game. Table 4 shows a comparison of student performance in pre and post-lab content tests for students who did and did not play the game. Within students who participated, 21 students who played the game submitted content tests while 11 students who did not play the game submitted content tests. From a basic descriptive analysis, students who played the game did see improvement between the pre and post tests (Cohen's $d = 0.539$). Further, students who did not play the game had better pre-test performance, but had little to no change after completing the lab assignment (Cohen's $d = -0.004$).

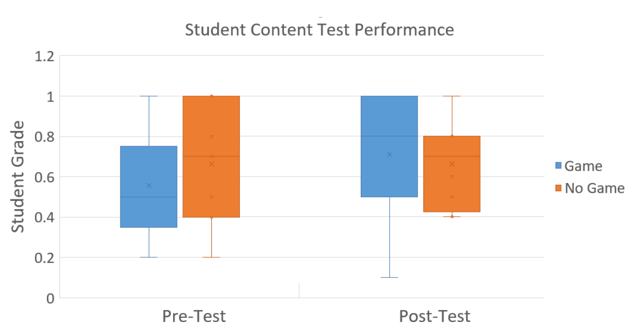

Figure 4: Comparison of pre and post-test results on a relevant content test for students who did and did not use Gridlock.

Students were also administered a self-efficacy survey that asked questions in three categories: 1. Confidence in ability, with questions such as "Do you feel that you have the skills necessary to succeed in engineering"; 2. Feelings of belonging, with questions such as "Do you feel that you think in the same way as other students in your engineering department"; and 3. Feelings of alienation, with questions such as "Do you feel alienated from engineering at your university". Students then rated on a scale of 1 to 7, 1 being strongly disagree and 7 being strongly agree. Table 2 shows average ratings for students who played the game (the treatment group) and Table 3 shows average ratings for students who did not play the game (the control group). Among these students, the treatment group contained 20 students who submitted both the pre and post-lab surveys; the control group had 7 students.

As shown, there was an overall increase in student confidence in both the treatment group (Cohen's $d = 0.147$) and the control group (Cohen's $d = 0.197$). In belonging, however, the game group saw a minor decrease overall (Cohen's $d = -0.089$), as did the control group (Cohen's $d = -0.104$). Finally, for feelings of alienation, the treatment group saw a slight negative change (Cohen's $d = -0.060$) while the control group saw a large negative change (Cohen's $d = -0.424$). Overall, the differences between the two groups can not necessarily be attributed to the administration of the game, though it can be said that the treatment group saw a greater increase in confidence despite the lower overall average rating. However, it can also be shown that the treatment group lacked a change in feelings of alienation, while the control group saw an overall decrease, but this could be attributed to the low number of students in the control group who submitted surveys.

Metric	Pre-lab	Post-lab
Confidence in ability	5.250 (1.552)	5.450 (1.146)
Feelings of belonging	5.517 (1.270)	5.408 (1.163)
Feelings of alienation from others	3.150 (1.655)	3.050 (1.651)

Table 2: Averaged pre and post-lab efficacy ratings for students who played the game. Standard deviations shown in parentheses.

Metric	Pre-lab	Post-lab
Confidence in ability	6.143 (0.886)	6.286 (0.518)
Feelings of belonging	5.976 (0.898)	5.881 (0.934)
Feelings of alienation from others	3.143 (2.010)	2.429 (1.274)

Table 3: Averaged pre and post-lab efficacy ratings for students who did not play the game. Standard deviations shown in parentheses.

Among a focused interview of 6 students, 4 said that the game presented more of a realistic engineering task than a textbook problem, with the other 2 saying that it was about the same. Further, 3 of the students said that the game was more interesting, more fun, and more educational than a textbook problem, with the other 3 saying it was about the same. Finally, 4 of the 6 students said the game had more resources readily available when compared to a textbook.

One final area of feedback regarding the game is the implementation of webcam access for emotion recognition and the security or privacy concerns related to that. In testing, students were asked to consent separately to the webcam access and image capture, with the option of disabling the feature if they did not do so. Further, the finished game system has plans in place to avoid the capture or storage of any images, instead opting to immediately extract emotion data and delete those images to relieve privacy concerns. Further, the option to disable this feature will remain in the game to ensure all students are comfortable with using the game system.

6. Conclusion

This paper shows results from the continued development of both the domain-specific game Gridlock and the Personalized Instruction and Need-aware Gaming (PING) system. The fully-incorporated PING system uses artificial intelligence methods to assist students in their learning process as they explore a virtual game environment and work to fix a broken traffic light controller. The newly incorporated Petri net model and reinforcement learning agents work in tandem to model a student's path through the game and make informed decisions on what support to provide.

The results presented are from early pilot testing within relevant courses. Preliminary results indicate that the game has a positive effect on student learning, however more data is necessary for statistically conclusive statements to be made. Future work with the Gridlock game will focus on increasing student participation in studies to collect additional data and showcase the game's effectiveness. Additionally, the team is also focused on developing the PING system into a standalone system that can be easily incorporated into other teaching subjects and other game environments.

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