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Evaluation of an AI-assisted Adaptive Educational Game System

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Abstract

As education continues to expand, both in outreach and in content, so too does the need for automated systems that can augment a student's educational process. This work builds on prior developments of a gamified adaptive tutoring system that automates and personalizes a student's learning process without instructor intervention. Our personalized learning system uses an augmented petri net graph structure to track student progress through the game, allowing us to enable or disable paths based on a student's performance. As an intelligent component, our system uses reinforcement learning agents to adaptively adjust system behavior based on student performance with the goal of optimizing student learning. The end result is a fully integrated game system that can measure student performance using integrated tests, leveraging that information to adjust game content, address learner misconceptions, and lead to a faster and more effective learning session. As part of continued research, we present data from pilot and comparison testing of our implemented game system.

With our comparison testing, we show that the game provides greater educational utility for students compared to a standard lab. To verify improved educational utility, we present results from content tests given pre- and post-intervention. We further verify the game system's educational utility through an example case of the game adaptation, showing the full process of adapting to a student and providing educational assistance. By sharing our testing and verification, we demonstrate the effectiveness of our intelligent educational game system. In addition, we provide developmental insights for other researchers in this area who seek to implement or improve their own systems.

1. Introduction

A recent trend in engineering education is the adoption of problem-based learning (PBL) approaches [1]. PBL immerses students in problem-solving by engaging them with a real-world (or simulated) problem scenario. Within PBL implementations, students are engaged in an exciting learning process as they explore the topics provided and work toward a possible solution. PBL approaches have seen great success in engineering education [2], [3], [4] and allow students to explore a solution space at their own pace, engaging in minimally guided exploration learning.

However, every student in a general education program has unique educational needs which may not be addressed by a discovery focused PBL approach. Researchers and school curricula will often focus on one-size-fits-all approaches to education which attempt to address all possible educational needs [5], [6], especially for PBL implementations. But even with major research into this area, one-size-fits-all approaches to learning are not able to address all possible unique educational situations or backgrounds. To expand general education and fit all possible students, it is necessary to explore automated systems to provide personalized student support for students whose educational needs are not fully addressed by a one-size-fits-all curriculum.

The main issue with a personalized-support-for-all approach to education is instructor resources; in a classroom of 100 students, an instructor could not possibly support every single student. Intelligent Tutoring Systems (ITSs) are one avenue for addressing the aforementioned issues [7]. These systems can already address the aforementioned issues, allowing students to explore at their own pace while also providing a certain level of structure or guidance to struggling students. However, ITSs can in many cases fail to fully engage a student in a learning process. Furthermore, ITSs may require instructor intervention if they fail to support a student, requiring instructor support anyway and reintroducing one of the original issues.

A logical advancement then is to combine a PBL approach to education with an ITS, allowing students to become engaged in the learning process while also providing structure and guidance to students who may be falling behind. One possible environment for combining an ITS and PBL is in a narrative virtual game environment. Serious games (SGs) [8] provide an ideal environment to combine these systems and address issues such as student engagement, personalized student support [9],[10],[11],[12],[13],[14], and even automated student assessment [15],[16],[17] without the need for instructor intervention.

Inspired by the above remarks, our proposed system is built on a narrative game called *Gridlock* [13] that focuses on a PBL approach to education. On top of the existing narrative game, we also implement an ITS to provide automated guidance to students as they play. With the complete system, referred to here as our personalized instruction and need-aware gaming (PING) system, we provide a system that actively monitors and controls student progress as students play through *Gridlock* using an internal Petri-net structure. As the student plays, the system gathers information using probing methods informed by social cognitive learning theory (SCLT) [18], creating sets of student information from which to make support decisions. When the student reaches specific points in the game, the system consults a reinforcement learning-based artificially intelligent (AI) agent to select personalized support based on the measured student data, addressing issues or misconceptions in the student's learning before retesting them to determine if they understand the material.

Section 2 provides an overview of our adaptive game system, including our system framework and a brief overview of the AI assistance. Section 3 provides results from our testing with *Gridlock* to show the impact of both game improvements and the system implementation, as well as some development insights from our testing. Finally, section 4 offers conclusions and future directions for this research.

2. Adaptive Game System Framework

The PING system and any augmented games are designed to operate automatically without intervention from instructors. The automated nature is designed to enable personalized student support without the need for heavy instructor intervention in the classroom. Furthermore, the intelligent components of the system should achieve similar results to a human tutor, offering targeted student support that fits a student's specific areas of difficulty.

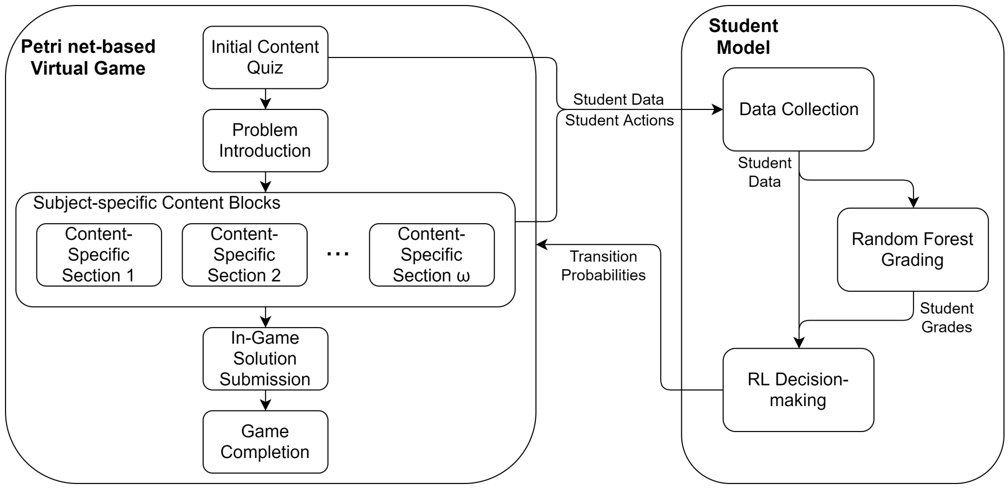

Figure 1: Augmented game system architecture [19]

Figure 1 shows an overarching view of the entire system. The system uses SCT-based probing to constantly gather student data and student actions within the game to inform an internal student model. While data collection occurs, the student undergoes an initial content quiz to establish benchmark data on their performance. The student is then introduced to the problem and taken into subject-specific content blocks, as chosen by the intelligent decision-making component. Each block addresses a specific subset of the overall knowledge required to complete the problem. Based on a student's performance in the initial content quiz, the system will enable or disable these blocks so the student only receives lessons on their area of difficulty.

In the case of our research, our general-purpose system is built and tested upon a domain-specific game known as *Gridlock*. *Gridlock* places students within Sustain City, a virtual city environment, in which they witness a traffic accident caused by a failure in a traffic light's internal controller. The students are then tasked with redesigning the logic controller in the traffic light. The traffic light logic design is commonly used as a lab project for students in courses related to digital logic and logic design, and as such the game is run in tandem with a lab assignment that assigns students to design a traffic light controller. At the end of the game, students design and program their controller using the Verilog hardware description language and submit it into the game where it can be checked for errors.

2.0.1 Student Data and Probing

As the student plays, the system records feature vectors for each of the subjects presented by the game, starting with the initial content quiz. In the quiz, the student is tested on each subject (In the case of *Gridlock*, there are 7 subjects all focused around digital logic design). The database then uses a random forest classifier to grade students, assigning them a grade from 1 (good) to 3 (bad) in each of the subjects presented. These grades then determine what subject-specific content blocks the student enters in to.

The data gathered by the game includes basic data such as scores on questions and quiz completion times. We also establish a more informed model with some expanded metrics such as confidence, where students self-rate their confidence on a question. In this way, a correct answer with a low confidence score could indicate guessing, or that they require more review to feel more confident in the material. Another metric used is a boredom/frustration metric determined by comparing the student's key presses and mouse movements against a recorded average. Finally, we also adapt an emotion detection system from Bahreini et al. [20] that captures images from a webcam and assigns emotional scores to students as they play. These scores focus around seven key emotions (happy, sad, surprised, afraid, disgusted, angry, and neutral).

2.0.2 Student Tracking and Directing

This section provides a brief overview of the internal structure used for student tracking. For more details, see our other publication [19]. Our student tracking models the game as a set of blocks shown in Figure 2. As students play through the game, their position is tracked relative to the block model, which focuses on a feedback loop of providing assistance and retesting to enhance a student's knowledge and ensure they learn the material. Furthermore, their position in the game can be directed through this model as well. For example, the subject-specific block shown in Figure 2 represents one of many subject-specific blocks; for example, *Gridlock* uses 7. Depending on a student's performance, the student is directed to different blocks to target their measured areas of difficulty.

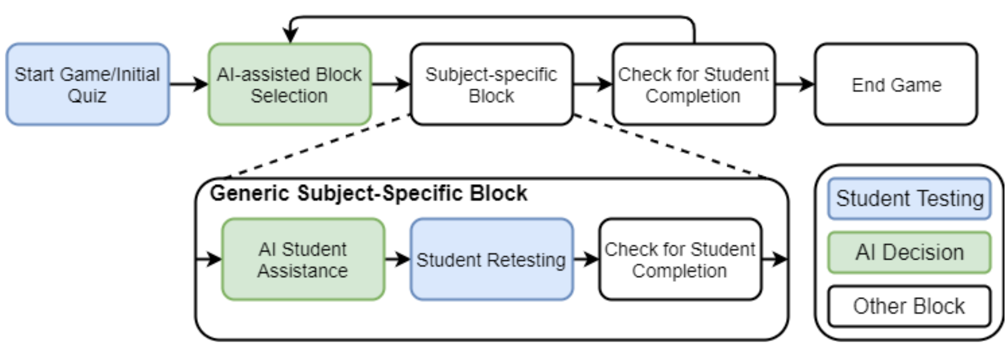

Figure 2: Block diagram showing how students are tracked through the game.

2.0.3 AI Assistance

The artificial intelligence (AI) component in the game is created through the use of reinforcement learning (RL). The RL agents in the PING system are the central decision-making component for the personalized student assistance. Referring to Figure 2, in each of the green blocks, the RL agent is tasked to make a decision. In the case of block selection, the agent chooses which block the student should prioritise; in the case of student assistance, the agent selects from a set of predefined help actions. Each of the help actions gives the student a brief dialogue about their perceived area of difficulty before giving them support in that area in the form of images, videos, and text depending on the chosen help action. All actions taken by the AI are based on the student's measured performance, and the AI gradually adjusts its behavior based on students' measured responses to the provided help.

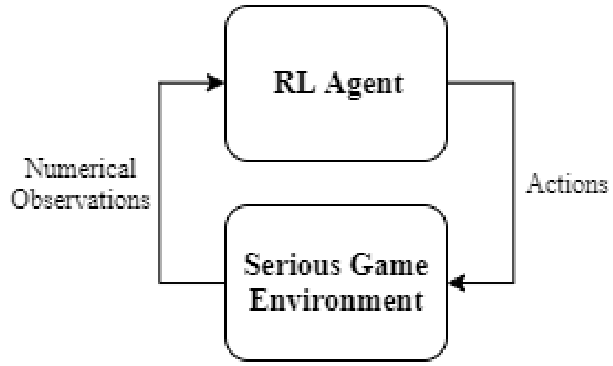

Figure 3: Top-level diagram showing the iterative learning behavior of RL agents.

3. System Evaluation

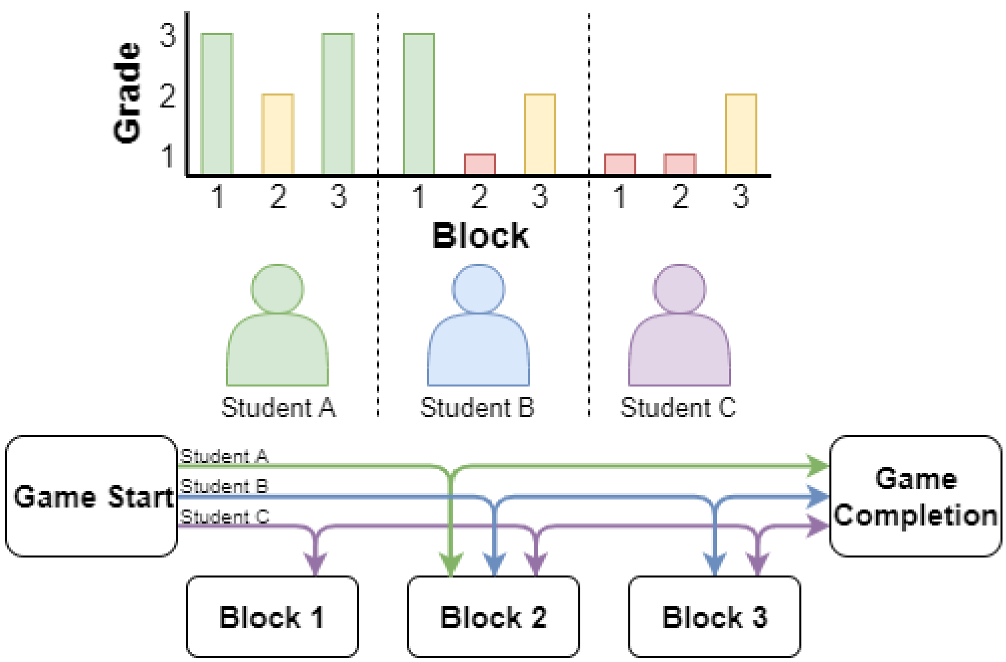

Figure 4: Example of AI-directed student movement in *Gridlock* using the first three subject-specific blocks as an example.

First, we provide a visualization of system functionality. Figure 4 shows the initial system grade on three subjects each from three different students. From there, the figure shows the path each student took through the game as determined by the education system. As shown, student A had high initial performance, allowing them to skip two of the three subject-specific blocks. Student C, meanwhile, had very low initial performance, leading to the system guiding them to all three of the subject-specific blocks.

Within the subject-specific blocks, students also receive varied dialogue depending on their performance as measured by the in-game evaluation. Figure 5 shows two different dialogues for different students at the same point in the game. As shown, the students received varied instruction on which content to review, as determined by their measured performance.

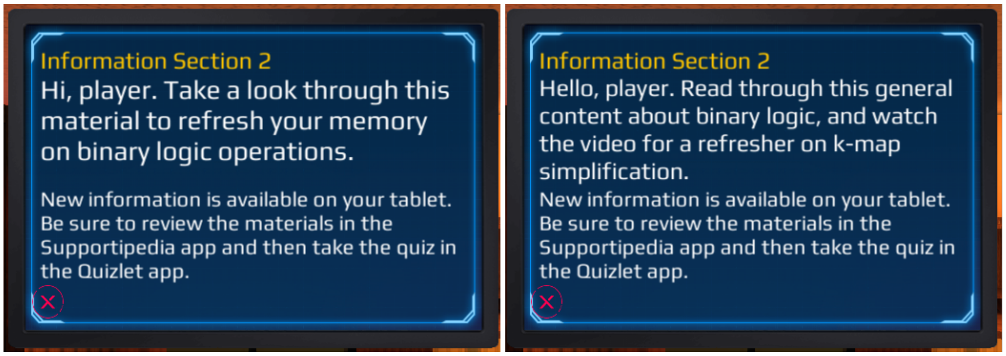

Figure 5: The in-game help dialogue in Gridlock, taken at the same point from two different students' perspectives.

Once a student has been given guidance, they are allowed to review in-game study materials composed of text, images, and educational videos. While students can freely browse the help documentation, the system also automatically directs them to specific areas depending on their performance. For example, the student on the left in Figure 5 would be directed to the help on binary logic operations while the student on the right would be directed to the video on k-map simplification.

Figure 6: The in-game help documentation in Gridlock.

We also tested students' content knowledge through pre- and post-lab content tests. We run a comparison test of student performance between students who both did and did not play the game, with the results shown in Figure 7. Among students who did not play the game, initial pre-test performance was markedly higher. However, these students showed little to no improvement in the post-test. Meanwhile, students who did play the game showed improvement from pre- to post-test.

Finally, as part of our results, we provide some brief perspectives on design and development of the game system. A key issue faced in testing of *Gridlock* was the game not providing proper

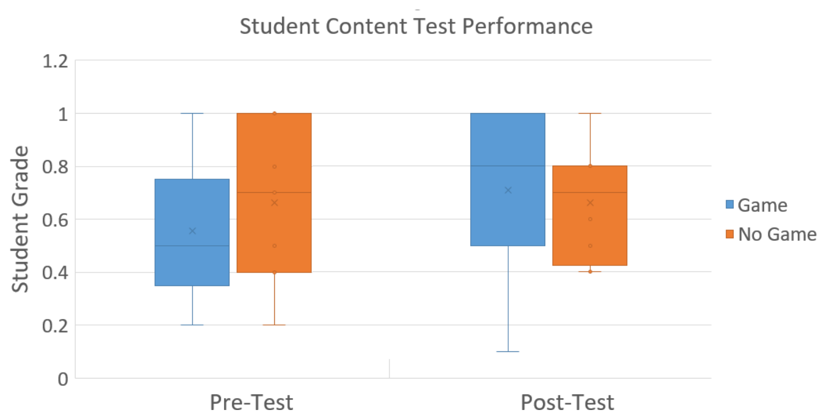

Figure 7: Comparison of pre and post-test results on a relevant content test for students who did (N=21) and did not (N=11) use Gridlock.

instructions on how to navigate the game environment or what was needed to progress in certain parts of the game. For example, at one part, students must complete subject-specific content blocks by interacting with computers to open said content blocks. Completed blocks are indicated by green lights, while incomplete blocks are indicated by red lights. However, the light indication was never explicitly explained to students, and several students were confused as to how to progress further. This was especially prominent among students who were not familiar with virtual games.

4. Conclusion

This paper shares results from our continued work to develop an AI-assisted intelligent tutoring system within a domain-specific serious game. Our personalized instruction and need-aware gaming (PING) system uses an internal Petri-net model and reinforcement learning agents to track and control student movement through the game while providing personalized educational support, all without the need for instructor intervention.

Our initial results from recent testing demonstrate a positive overall trend between the prior game version and the new version, showing positive reception on both our recent developments and our integration of the intelligent support system. As work continues, we seek to improve the effectiveness of the AI assistance and further generalize our overall system for use by other researchers in other serious game systems. Furthermore, we aim to improve student engagement through more interesting and varied evaluation tests, as well as exploring additional ways to deliver content in a virtual game environment.

5. Acknowledgement

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