A Personalized Learning System for Parallel Intelligent Education

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***Abstract*— Technological advancement has given education a new definition—*parallel intelligent education*—resulting in fundamentally new ways of teaching and learning. This article exemplifies an important component of parallel intelligent education—artificial education system in a narrative game environment to offer personalized learning. The system collects data on the player's actions while they play, assessing their concept knowledge via k-nearest-neighbor (kNN) classification, and provides tailored feedback to that student as they play the game. Based on an empirical evaluation, the kNN-based game system is shown to accurately provide players with differentiated instructions to guide them through the learning process based on the estimation of their knowledge levels.**

***Index Terms*— Adaptive game system, k-nearest-neighbor (kNN), parallel intelligent education, personalized learning.**

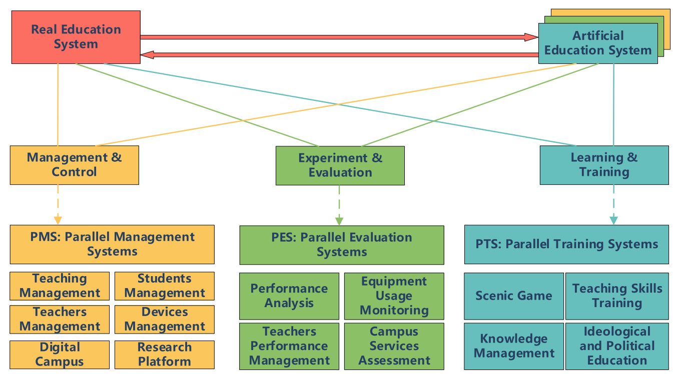

Fig. 1. System platform of parallel intelligent education.

I. Introduction

THE issue with traditional class structure is that a single instructor utilizing a single teaching method is very likely to be ineffective to at least some of the students in the class; not all students learn in the same way, nor do they require the same instruction methodologies. Although a gulf in learning effectiveness may exist between individual students, it has been shown that guided learning methods benefit more students than discovery learning [1], [2]. Some students prefer a guided, structured approach, with instructors providing direct instruction. Other students are highly self-motivated and benefit from freedom and opportunities for discovery. Some students lack motivation or prior knowledge, accentuating the need for direct instruction; and some students will achieve very little on their own, instead of becoming frustrated and giving up [3]. The "just-in-time" instructional model has been shown to be effective in meeting individual needs or needs of small groups [4]. Even with these methods though, instructors often have limited access to time and resources necessary to implement these methods on larger class sizes [5].

With the radical and transformative technological advancement, such as artificial intelligence (AI), big data, and internet-of-things (IoT), many new concepts, infrastructures, technologies, and devices are emerging to help in the students' instruction and support their learning 24/7. All of those lead to a brand-new definition of education—parallel intelligent education—as shown in Fig. 1. The interaction between real learning and virtual learning via various pedagogical tools empowers the next generation of digital citizens in more effective and efficient learning; two of these tools are intelligent tutoring systems (ITS) and narrative virtual environments.

The end goal of ITS is to either enhance or entirely replace the instructions of a human tutor; the ITS would share responsibility with instructors to support a guided learning approach. Typically, these ITSs operate by identifying the strengths and weaknesses of individual students and offering help to those students based on the strengths and weaknesses. ITS systems such as Autotutor [6], Annie [7], and Andes [8] have shown their effectiveness for individual students; however, they fail when students lack the motivation to seek out the help these systems provide. Students might not even know where to start when seeking help. Lower performing students might be so perplexed with a problem, and they cannot even phrase a meaningful question. In this case, an ITS might offer irrelevant help, or incorrect help, harming the student more than helping them. Furthermore, students may take advantage of typical ITSs, for example, using all hints

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(A)

The sequence of lights switching per 5 clock cycles and starting at the Red-Red reset stage	
Side str. Light	**Main str. Light**
Red	Red
Green	Red
Yellow	Red
Red	Red
Red	Green
Red	Yellow

(B)

Fig. 2. (a) Street intersection and the narrative. (b) Light switch logic.

offered to them to just solve the questions and get the learning over with. This creates a shallow learning curve and is one of the main talking points against ITSs [9], [10]. Therefore, rather than allowing students to chart their own path through the learning process, it is instead better to observe their behavior and understand what help they might need. This comes into play for open-ended questions, such as those asked in engineering education. While researchers have been looking into assessment and tutoring within poorly structured domains and problems [11], [12], the issue of providing personalized assistance via adaptive systems in engineering education has yet to be addressed, although steps have been taken in other areas [13].

ITS systems have been proven as strong teaching tools, but they lack the ability to solve student engagement issues [14]. Student engagement remains to be one of the greatest issues within classrooms, serving as a barrier to all forms of education, regardless of student's intellect. Thus, if the strengths of an ITS are to be fully exploited, an additional structural layer is required. A narrative-based virtual environment would offer such a structural layer. These narrative-based virtual environments embody real-world situation for players to explore; ultimately inviting the players to become engaged in a combination of learning and effective problem solving. Examples of such development can be seen in Crystal Island [15] and Sustain City [16]. The topic of considering games as an engagement and learning tool has become popularized under the umbrella of "serious games," or educational games [17]. Research has shown that by attempting to combine realistic simulations with the motivational and goal-based features often found within commercial video games, player engagement is greatly increased for practical purposes and open-ended problems [18]. The cause, most evidently, is that narrative-based virtual environments provide a more entertaining method of presenting material to students and getting them to solve domain problems [19].

Although domain problem solving is important, just solving problems cannot lead to improved skills or deeper subject understanding [20]. True learning requires the learner to be actively involved in the problem-solving process. The learner must also receive feedback from the system on increasing their metacognitive proficiency. Despite the obvious strengths of both ITS and "serious games," there is a conspicuous absence of both metacognitive interventions for learning and rigorous evaluations within narrative games; however, there have been attempts at integrating popular ITS tools with game engines [3], [21]–[23]. A combination of a metacognitively focused ITS system with an experimental, narrative-based learning game opens a new path for personalized learning, building upon and augmenting previous attempts. Such a combined system corresponding to "learning and training" module in Fig. 1, if designed, must have an effective mechanism to gather and reason information on learners' behavior but not interfere with the narrative, corresponding to the "experiment and evaluation" module in Fig. 1. Finally, the system ought to provide learners individualized scaffolding that guides them through the problem-solving in game, corresponding to the "management and control" module in Fig. 1. The focus of this article is the creation of such a system and its implementation in a previously implemented narrative-based educational virtual environment called gridlock, which features engineering design in the digital domain. The rest of the article is organized as follows: Section II talks about gridlock, Section III presents the adaptive, k-nearest-neighbor (kNN)-based game system, Section IV presents system assessment, and Section V is the conclusion.

II. Overview of Gridlock

Traffic lights represent a universally understood concept, and gridlock makes use of that concept to teach students the basic methodology and theory behind sequential circuit design. Gridlock features a central task, whereupon a student would investigate how to fix a traffic light for a four-way intersection, as shown in Fig. 2(a). The first-person game, built using the Unity 3-D engine, allows the player to witness a serious traffic accident, calling upon them to redesign the traffic light controller with the correct logic. Fig. 2(b) shows the correct solution to the problem, which the player would design in the form of a finite state machine, using their prior or newly obtained knowledge of sequential logic design.

Learning is a fundamental cognitive process of human intelligence. Research indicated that the more students are aware of their thinking process, the more they can control such matters as goals, dispositions, and attention, and the more they sharpen their mind to learn [24]. Such awareness and monitoring processes are often referred to as metacognition. Considering this, several metacognitive interventions are naturally integrated into gridlock.

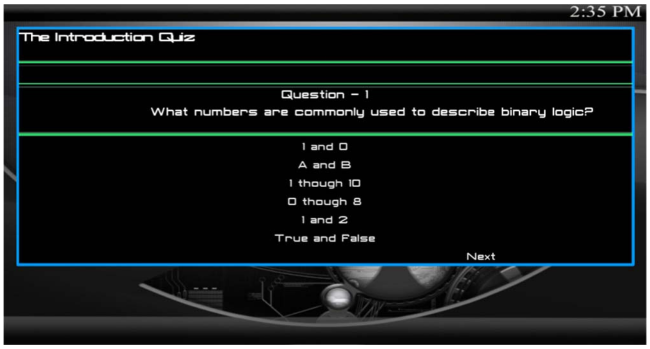

Fig. 3. Sample question prompt in gridlock.

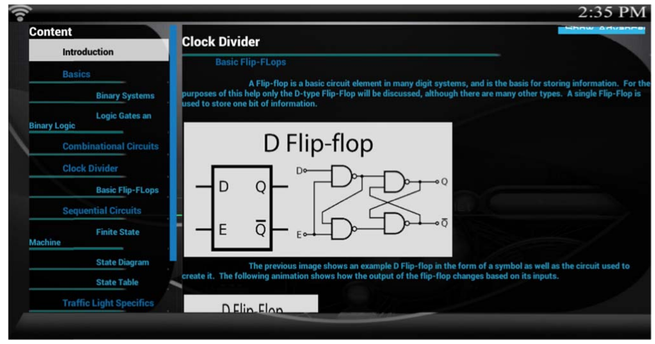

Fig. 4. Learning roadmap help documentation in gridlock.

A. What I Know–What I Want to Know–What I Have Solved Training

What I Know–What I Want to Know–What I Have Solved (KWS) is adapted from a well-known reading strategy, What I Know–What I Want to Know–What I Have Learned (KWL) [25]. This intervention is usually implemented into the traditional classroom by handing out a three-column chart structure to students. The left column is used to activate students' prior knowledge by recalling what they know about a problem (K). The middle column asks students what they want to know (W) in the way that motivates them to read and think more. Finally, students summarize what part of the problem has been resolved and what is yet to be solved (S) in the right column. The implementation of KWS in gridlock is accomplished through a series of progressive prompts at key game stages, as exemplified in Fig. 3. The game further assists students through the learning process by dividing up the problem into manageable steps: comprehension of the problem statement, state machine design, and state table design. At each of these steps, the player receives question prompts that are tied closely with the overall goal, further cementing their knowledge of the facts and concepts relevant to that problem-solving stage. The game system then recommends the player to move forward or remain and study further based on their responses to the prompts. Many educational games feature a similar structure, giving users intermediate tasks to complete before they can solve the final problem.

B. Learning Roadmap

The roadmap is composed of a set of milestones and actions, providing students an expert view of what takes to solve a problem. In gridlock, the map provides study guides that endow students with the capability to find relevant information and to capture key concepts in the study material [26], as exemplified in Fig. 4. This, therefore, caters extremely well to the majority of students that adopt sequential learning. Stressing the big picture of the goal and the relevant facts to the larger whole is an important addition to address the minority of global learners who might otherwise be frustrated by the traditional methods.

C. Supplemental Feedback

Considerable research evidence shows that effective feedback supports a wide spectrum–the cognitive, behavioral, and motivational aspects of self-regulation, leading to ample learning gains [27]. To that end, experiential consequentiality and various feedback mechanisms are threaded through gridlock. While a player interacts with the KWS training, the responses from the game system help him reflect on his own content knowledge and decide whether it is sufficient for the task being assigned. Eventually, when the player submits his design, the system evaluates it and allows him to visualize the consequences. In particular, the simulated traffic lights that respond to a good design operate according to the correct sequence and timing given in the specification; otherwise, an accident occurs due to the incorrect logic design. In addition, the game system categorizes his errors and offers him suggestions for potential error correction. Providing feedback on student design performance, along with opportunities to repeat the "task-performance-feedback cycle" by allowing resubmission, is good practice in enhancing student self-regulation [28]. It is in such a project, where students are engaged with societal and community concerns, they are able to realize the importance of their knowledge to make a difference in people's life. Providing added meaning to the problem gives the students more enthusiasm in learning material.

III. KNN-Based Adaptive Game System

The biggest challenge presents when designing an intelligent learning game is the identification of both when a player needs assistance and what assistance that specific player needs in that specific situation. Any data relevant to the learning process are often only available through direct observation of the learning process, and which data will be useful may vary from player to player. Thus, any attempt at developing an accurate solution to estimating student knowledge must allow the game system to (1) utilize past experience to a specifically defined set of data structures while also (2) exploiting the knowledge captured in this data set to improve the overall estimation performance of the system. To accumulate data from the players, the problem must be broken into subsections to thoroughly evaluate player behavior on a section-by-section basis. In the case of gridlock, there are three distinct sections. In order to tackle the design problem, a student must have the fundamental knowledge of digital logic, such as binary signals, logic gates, and Boolean algebra. The first section, then, centers on the basic domain knowledge and ensures

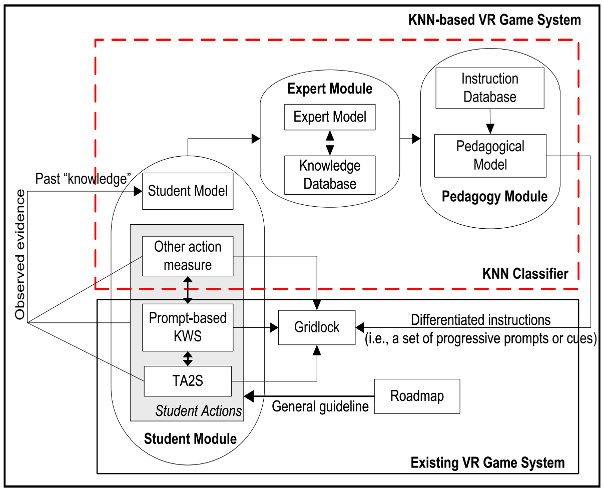

Fig. 5. System architecture of the kNN-based virtual reality (VR) game system.

that each player has a solid grasp on the concepts before attempting to design the circuit. The second section focuses on the tools for sequential circuit design (e.g., state machine and state diagram) as the traffic light controller is a typical sequential circuit. The last section covers information that is more specific to the problem itself.

At each of the individual subsections within the game, data are gathered from each player and used to evaluate them on their knowledge of the concepts presented within the section. The results shown by this evaluation, as well as other measures of the player's behavior are used to classify the player, determining if the player has mastered the concepts within that section of the game. The classification is cascaded from one stage to another, as the later stages represent knowledge that builds upon the previous sections' concepts. If a student is classified such that their concept knowledge is shown to be low, the student is presented with immediate feedback and assistance, allowing them to acquire that knowledge. This knowledge-based classification is implemented within gridlock through a kNN-based closed-loop control shown in Fig. 5. This system consists of three modules: the student module, the expert module, and the pedagogy module.

Many classification methods could be utilized in providing the knowledge-based classification necessitated by the proposed system. The main factor in the choice of kNN over other possible classifiers is the continuously evolving nature of the system. As a lazy classifier, kNN is simply relative to other widely used classifiers. A kNN classifier allows for online updates at minimal computational complexity. Thus, as new data are gathered, it can be scored by a human professional and immediately utilized in scoring new players, skipping long training periods that would affect other classifiers.

A. Student Module

The student module provides various measures to capture data from students in real time. The features from these data are then selected as features for the type of classification in the expert module.

As stated earlier, a pool of well-designed question prompts are constructed closely tied to goals, knowledge, and facts that are part of problem solutions specific to the game. The game system then randomly selects a list of them and prompts to a player. The focus is to draw out the cognitive processes of respondents as the player answers the questions. When students take significantly longer than average to respond to a component of the problem, it is a sign of them running into technical difficulty or lack of time management and focus. Therefore, another important feature our game system uses is the amount of time a player spends on individual tasks. In addition, the game system detects sporadic rapid mouse movements and keyboard strokes over periods of time in order to determine the level of frustration. It is assumed that the player's frustration level is increased if keys that are unrelated to the game are being pressed rapidly and erratically. The similar assumption applies to sporadic movements of cursor positions.

The responses to the assessment queries are recorded and kept as a model of that student's learning. Further assessment responses are accumulated with the prior knowledge and used for future decision-making.

B. Expert Module

The purpose of the expert module is to attempt to predict the solution path that a student is pursuing. Using the path prediction, the module then offers help to the student when they are stuck or deviating from the path. This method requires the problem to be well known, and all solution paths to be well defined. However, as problems could have a near-infinite number of solution paths, mapping students to one of these paths could be cumbersome, time consuming, or computationally intensive. Instead, the proposed expert module uses a different approach; regardless of the nature of the problem, it can be solved through four steps: 1) understanding the problem and identifying necessary information; 2) connecting the known and unknown information; 3) heuristic execution; and 4), review for improvement [22]. Thus, the following can be defined as essential abilities for any problem solver to acquire correct solutions:

1) Setting part of the problem solution as a goal;
2) Identifying that a fact is part of the problem solution;
3) Applying and utilizing a rule or strategy within the specific problem-solving context.

Therefore, the expert module attempts to find out if the student correctly grasps all the necessary information needed to complete the given task, as opposed to determining the specific solution path the student is pursuing. In this case, the decision-making can then be modeled as a classification problem, using data gathered from the user within the game environment to decide how well the student knows the provided material.

As a suggested solution, a complex problem can often be divided into smaller problems. Fig. 6 demonstrates a divide-and-conquer method that is utilized within the expert module. The game system is split into logical sections $S = \{s_1, s_2, \ldots, s_r\}$, wherein each section contains a smaller problem that needs to be solved. By combining all the smaller

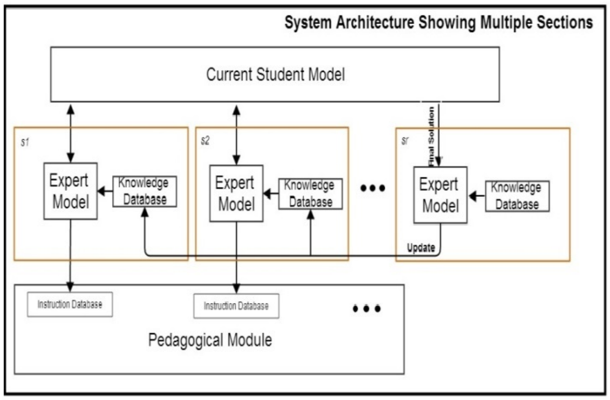

Fig. 6. System model showing the cascading individual sections.

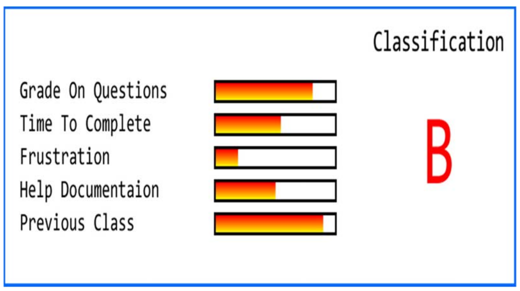

Fig. 7. Classification example.

solutions from each section, the final solution to the original problem can be produced. Thus, the expert module is composed of r instances, each containing a knowledge database and an expert model that is built specifically for that section of the problem. The expert model conducts student classification with the kNN classifier, and the knowledge database contains the training data set for said classifier, $T^{s_h} = \{X^{s_h} \mid X^{s_h} = (x_i^{s_h}, \text{class}(x_i^{s_h})), i = 1, 2, \ldots, n\}$ that corresponds to a particular problem section s_h, $\text{class}(x_i^{s_h}) \in C^{s_h} = \{c_1^{s_h}, c_2^{s_h}, \ldots, c_m^{s_h}\}$ represents the classification of x_i, and x_i is a d-tuple feature vector $[f_1(x_i^{s_h}), f_2(x_i^{s_h}), \ldots, f_d(x_i^{s_h})]$.

By cascading these individual expert module instances, the outcome from one section can both be used to provide individual assistance to the student within that section and also to provide an input feature to the next section. Fig. 7 shows the classification features used in a problem section s_h $(h = 1, 2, \ldots, r-1)$, including question prompt score, question prompt completion time, where the student looked within the help documentation, the previous classification, and if the system found that the student was frustrated. Individual weights are also applied to the features. For instance, grade is weighted around 10 times higher than other features, as it represents an objective measure of student knowledge when compared to the others. By the end of the last problem section, s$_r$, the system will have a classification that accurately represents the student's overall content knowledge. This information, and the data gathered, can be used to update the knowledge database. As more data are gathered from more users, the training data grow, and the system continues to learn and evolve. The cascaded kNN algorithm used is explained in pseudocode in Algorithm 1.

Algorithm 1 Cascaded kNN Pseudocode

1. **For**(each value in testing data set)
   a. **For**(each value in training data set)
   b. Compute Euclidean distance between the testing data point and the training data point, using equation 3.1.
   c. **End For**
2. Select the k nearest neighbors of the testing datapoint.
3. Majority vote to assign a class to the testing datapoint using equation 3.2.
4. **End For**
5. Pass classifications on to the Pedagogical Module.

$$D = \text{dis}(x_0 - x_i) = \sqrt{\sum_{j=1}^{d} (\omega_j f_j(x_0) - \omega_j f_j(x_i))^2} \quad (3.1)$$

where d is the number of features, ω_j is the weight for the jth feature, x_0 is the current testing datapoint, and x_i is the ith training datapoint

$$\text{class}(x_0) = \arg \max_{j=1,2,\ldots,m} \sum_{i=1}^{k} \delta(\text{class}(x_{0i}), c_j) \quad (3.2)$$

where δ is the Kronecker delta, k is the number of nearest neighbors, x_{0i} is the ith nearest neighbor to x_0, and c_j is the jth class.

The kNN classifier then allows for flexible evolution of the system. As new "knowledge" is observed, it can be immediately added to the training data and used for classification. In the case of this system, whenever a user completes the game, their data are added into the database. The training set expands as more users play the game, increasing the number of distance calculations needed for classification. Because this rapid growth could easily cause the kNN to become computationally intensive, any and all improvements to the efficiency of the distance calculation are vital to the overall speed of the kNN system. A very simple improvement utilized is to use squared Euclidean distance, producing the same result, but avoiding the final square root used in normal distance calculations. Furthermore, most game engines have built-in calculations for vectors with length 4 due to the common nature of distance calculations within games. Taking advantage of these highly optimized calculations built into the Unity 3-D engine, the speed of the kNN calculations can be further improved. Combining these optimizations, Algorithm 2 demonstrates the final augmented Euclidean distance calculation that is implemented within gridlock.

With this data separation, an overhead is present relative to the number of dimensions involved. As such, the overall efficiency of the system would be much lower with high dimensional data, but as we only utilize vectors of length 5 or 6, the overall improvement is significant. For example, using a vector length of 6, performing 100 000 distance calculations within Unity 3-D was 60 ms with the normal

Algorithm 2 Augmented Squared Euclidean Distance Calculation

Input:
x_0 : testing data
x_i : training data
Output:
1. $y = \lceil d/4 \rceil$
2. Set $D_l = 0$ where D_l is the augmented Squared Euclidean distance between x_0 and x_i
3. **for** $l = 0$ to y
    $Start = l*4$
    $Finish = Start+3$
    if ($Finish <= d$) **do**
        $D_l = D_l + sqrMag(x_0[Start : Finish] - x_i[Start : Finish]$
        where *sqrMag*() is the function of squared magnitude of a vector in Unity 3-D. In this case, this gives the same result as the Euclidean distance between the two points.
    else do
        z_0={$(x_0(Start : d), zeros(Finish - d)$}
        z_i={$(x_i^{Sh}(Start : d), zeros(Finish - d)$}
        $D_l = D_l + sqrMag(z_0 - z_i)$
4. **end for**

method and 14 ms with the augmented method. While these results would depend on the game engine, the computational hardware, and the implementation, the overall improvement is still significant.

C. Pedagogical Module

The objective of pedagogical module is to recognize on which part of the solution a student is having difficulties, and then to offer hints that are tailored specifically to his needs. Although the instruction database contains all necessary learning material that is readily available for players to explore, not every one of them proactively searches and uses it. In fact, the students who need help the most are least likely to seek it due to various factors. For instance, low-performing students often could not get a grip on the situation, thus they are lost on the subject to know what information to look for. This is where adaptively mapping student needs to relevant study guides becomes extremely important. Upon classification in the expert module, the system indeed forces the student to look at a specific learning material that is pertinent to the knowledge that the system thinks he lacks.

IV. Assessment

To date, gridlock has been piloted in a focus group as well as two sections of a computer architecture class. A mixed methodology was utilized for evaluation and assessment that triangulated understanding of how the personalized system in parallel education impacted student learning. In particular, the following two research questions were used to guide the project assessment.

TABLE I
Results From the Focus Group Test

User ID	Level	Pre-Test Score	Classified Level
Ant	High	36/40	A
Amritkar0		38/40	A
Chrsiten0	Average	35/40	B
Bat		32/40	B
Pat2		28/40	C
Mahmud2	Low	20/40	F
Trev		5/40	F

*Question*1: How well is gridlock to provide the same instructions to different students who master similar domain knowledge and differentiating instruction across dissimilar solution paths?

*Question*2: If gridlock can accurately and consistently provide personalized coaching in the game environment, to what extent does the personalized system in parallel education enhance students' learning skills and achievements?

A. System Accuracy

Part of evaluating the accuracy of the kNN classification was the establishment of a focus group of seven students. The seven students were chosen based on academic performance, with three average students, two high-level students, and two low-level students chosen. Table I shows these students' classifications compared to their pretest scores. As shown, the high performing students received A classifications, the average students received B and C classifications, and the low performing students received D and F classifications.

The efficacy test of gridlock was conducted in a computer architecture class at Rowan University. The students within the classes were assigned a pretest on the concepts and skills of digital logic design before playing through the game and took a similar posttest after playing the game. Students were observed during the game playing and their before and after scores were both recorded. While playing through the game, the game also gathered various data points, including estimating the students' perceived frustration levels and measuring the time taken to complete parts of the game. Using data gathered from the 24 students that played the game, Fig. 8 shows a comparison between the concept-based pretest scores that students achieved and their initial knowledge classifications within the game, demonstrating the accuracy of the classifications.

In Fig. 8, a classification of 1 represents high concept understanding or an "A" grade. A classification of 5 represents low understanding, or an "F" grade.

B. Students' Concept Understanding and Learning Skill

Table II shows the pretest and posttest results from the two computer architecture classes, where group one did not play through the game and learned the concepts in a traditional learning environment and group two did play through the

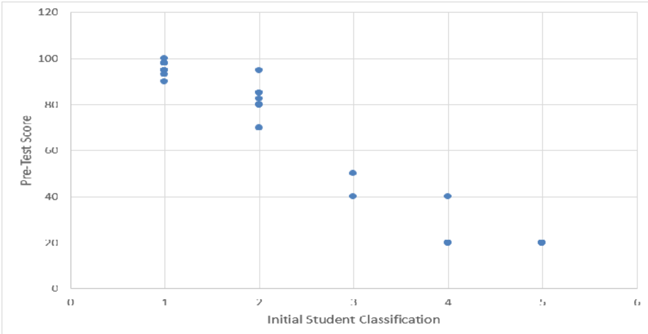

Fig. 8. Initial student classifications compared to pretest scores.

TABLE II
PRETEST AND POSTTEST RESULTS FROM BOTH CLASS SECTIONS

Group 1 (No Game)			
	Pre-Test	Post-Test	% Difference
Min	2%	10%	+133.3%
Max	95%	100%	+5.1%
Average	48.8%	58.8%	+18.6%
St.Dev	33.8%	34.6%	+2.3%
Group 2 (Game)			
Min	20%	75%	+115.8%
Max	100%	100%	0%
Average	71.9%	92.5%	+25.1%
St.Dev	30.2%	7.1%	-123.9%

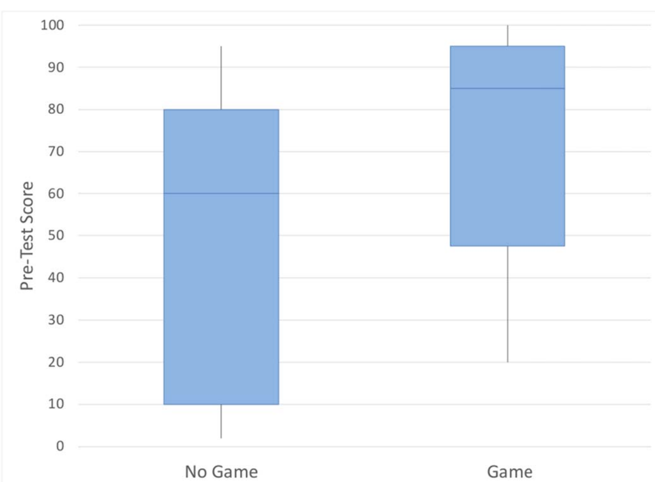

Fig. 9. Box-and-whisker plot for the pretest scores from both groups.

game, so its learning consists of both traditional and virtual parts. Both classes were taught by the same professor. Group one consisted of 14 students and group two consisted of 24 students.

Fig. 9 shows a box-and-whisker plot of the pretest scores from both sections. Fig. 10 shows the same plot, but for posttest scores. As shown in Fig. 9, the pretest scores for

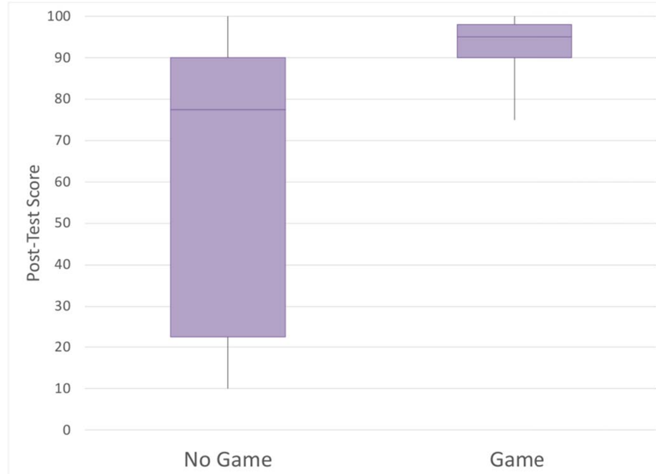

Fig. 10. Box-and-whisker plots for the posttest scores from both groups.

TABLE III
FINAL PROJECT REPORT GRADES FROM BOTH TREATMENT AND CONTROL SECTIONS, SHOWING GRADES OF DESIGN-FOCUSED SECTIONS OF THE REPORT

	Group 1 (No Game)	Group 2 (Game)
Average Overall Grade	70.4%	84.6%
Verilog HDL Code	83.2%	99.0%
Design and State Table	54.1%	89.5%

both sections had fairly high deviation, with a large difference between the maximum and the minimum. However, the section that played the game showed higher initial scores before playing the game. The posttest scores, meanwhile, saw significant improvement in the treatment group that played the game. The standard deviation was also significantly lower in the posttest results for the treatment group, showing class-wide score improvement and demonstrating that students were assisted by the use of the game. Meanwhile, in the section that had a standard lab instead of playing the game, there was little improvement overall in the posttest scores.

For statistical proof, a two-sample t-test was done for the pretest data and the posttest data. For the pretest data, the two-tail p value was calculated at 0.06, proving no statistical difference between the mean score in group one and group two. For the posttest data, the two-tail p value was calculated at 0.004, proving a statistical difference between the mean score in group one and group two. The game, therefore, had a statistically significant impact on student performance within the treatment group.

To further demonstrate the effectiveness of the game upon student learning, the students' final report grades were also taken from the class sections. In the case of this computer architecture class, the final project was highly related to the digital logic design concepts presented to the students by the game. Table III shows the students' average scores in the final report from both sections, as well as their percentage scores of the more design-focused sections of the project.

As shown, the students that experienced both traditional and virtual learning achieved overall improved grades on their final design projects, with better scores on both their final designs, their presentation of those designs, and their Verilog code implementations of their designs. The improved performance of the treatment section represents the overall goal of the personalized learning in parallel education to improve student comprehension and understanding of topics. Higher scores on design-focused sections of the project and report shows improved understanding of concepts and implementation, which the game focuses on by assisting students with their state machine and Verilog designs. The result is that the students achieved overall higher scores, not just in concept tests but in project-based application of their learned concepts as well.

V. Conclusion

More and more students cannot fit a "one-size-fits-all" teaching model that offers only minimal, identical instructions to every student in each class. The need, importance, and potential benefits—as well as the difficulties for obtaining the resources—for providing a more personalized learning framework that better meets students' educational needs can be hardly overstated. It is, after all, the first of the fourteen Grand Challenges set by the National Academy of Engineering for the 21st century [29]. Parallel intelligent education, on the other hand, presents a solution to this challenge. In particular, its virtual learning opens a new way of collecting significant bits of knowledge into student conduct and performance so that it can differentiate students by their aptitude and offer personalized guidance. This article exemplifies such education theory in a narrative game environment, where a kNN-based student model is built to promote self-directed learning. Specifically, the student model systematically reasons about the multitude of factors that bear on decision-making from the students' game-playing behaviors in problem-solving to infer their domain knowledge and plans. It then adapts through a set of question prompts and cues customized to individual learners in specific contexts. Pilot results from student content tests and focus group interviews show that parallel education, including both traditional and virtual learning, is effective in promoting student strategic thinking and problem solving.

The research can be extended in several directions. The proposed model is designed to be easily modifiable for other courses outside of the one given in the presented scenario. However, when the size of data sets increases in the case of much larger courses or student groups, the kNN classifier, even with squared Euclidean distance calculation, can present issues with inaccurate classifications and extremely increased computation time necessary for classification. Augmenting the proposed system with approximate nearest-neighbor (ANN) algorithms such as fast library for approximate nearest neighbors (FLANN) [30] or locality-sensitive hashing (LSH) [31] is necessary. The use of ANN in place of standard kNN would provide increased scalability of the model to larger data sets. Rigorous assessment and characterization of players' activities are vital to offer "just-in-time" instructional support tailored to learners' needs. Such assessment can be in-game measures, such as recording game session and tracking players' in-game performance that are utilized in our article. More external measures, such as facial emotion detection [32] and neurophysiological sensors [33], [34], and their applicability to the educational environment are worth of investigation. More pilots need to be conducted for data analytical studies to further test our theory and methodology. Both reinforcement learning [35] and deep learning [36] technologies are necessary to be explored for system optimization.

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