Implementation of Stable Pairing Algorithms for Optimizing Educational Games: A Computational and Pedagogical Perspective

Luiz Carlos Pinheiro Junior, Everton Gomede, and Leonardo de Souza Mendes

Abstract— **The Gale-Shapley algorithm solves the problem of stable pair formation across various fields including economics, labor markets, biology, computer science, and physics. This study modifies the algorithm to use a single list of participants and calculates compatibility scores using Jaccard similarity coefficients from students' proficiency tests and academic performance. We compared the effectiveness of this modified algorithm by evaluating two groups of students engaged in digital educational games: an experimental group matched by the modified algorithm and a randomly matched control group. The results show that the modified algorithm forms pairs with superior compatibility, consistent performance, and balanced competition. These findings suggest integrating the Gale-Shapley algorithm into educational technologies can enhance learning environments. The results significantly impact educational practices indicating that systematic peer training can improve collaboration, competition, and student engagement.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9196

Index Terms— **Gale-Shapley algorithm, stable matching, digital game-based learning, digital games, compatibility measures, competitive learning.**

I. Introduction

Forming document stable pairs poses a fundamental challenge in several fields, including economics, the labor market, and education. David Gale and Lloyd Shapley developed the widely used Gale-Shapley algorithm in 1962 to solve the Stable Marriage Problem (SMP) [1]. Its influence extends beyond mathematics and economics as it optimizes combinations within complex systems in biology, computer science, and physics [2]. The Gale-Shapley algorithm establishes stable pairings in education that foster effective student engagement and collaboration [3], [4]. The rapid growth of educational technologies, including digital games, creates new opportunities to engage students and enhance learning outcomes [5], [6], [7], [8].

The compatibility between study partners significantly influences learning effectiveness [9], [10]. Incorporating digital games in educational settings introduces a competitive element that enhances critical skills and promotes active engagement. Aligning competition with educational objectives allows educators to use it as a motivational tool, challenging students and fostering a dynamic educational environment. This approach boosts motivation by recognizing and rewarding skills and achievements [11]. Games and virtual worlds also provide interactive environments that enhance academic performance and facilitate understanding complex concepts [12], [13]. However, establishing systematic student pairings is necessary to enhance academic performance and social interaction.

This study aims to adapt the Gale-Shapley algorithm to incorporate similarity measures that calculate compatibility scores and evaluate its effectiveness in forming stable pairs in educational and competitive contexts. Specifically, we propose modifying the algorithm to use only a list of participants and compatibility scores based on Jaccard's similarity coefficients from student proficiency and academic performance tests. Our primary objectives are to evaluate the efficacy of this modified algorithm in forming stable pairs in educational and competitive contexts, particularly in English classes using digital games, and to compare the learning outcomes and engagement levels of students paired by the modified algorithm with those paired randomly.

This research is significant in several critical areas within education and computer science. By exploring the effectiveness of the modified Gale-Shapley algorithm, we contribute to the existing knowledge on pairing algorithms and their applications in educational contexts. Promoting healthy competitiveness will result in greater student engagement and enhanced learning outcomes. This study evaluates the impact of pairing based on similarity measures on the efficacy of educational games. The findings can inform educational practice, suggesting that integrating pairing algorithms with educational technologies may result in more effective and engaging learning environments.

II. Literature Review

Digital games have emerged as powerful tools for teaching and learning, providing interactive environments that increase

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L. C. Pinheiro Junior is with the Universidade Estadual de Campinas, Campinas, SP, Brazil and Instituto Federal do Paraná, Telêmaco Borba, PR, Brazil (e-mail: luiz.pinheiro@ifpr.edu.br).

E. Gomede is with the Universidade Estadual de Campinas, Campinas, SP, Brazil and University of British Columbia, Vancouver, BC, Canada (e-mail: everton.gomede@ubc.ca).

L. S. Mendes is with the Universidade Estadual de Campinas (UNICAMP), Campinas, SP, Brazil (e-mail: lmendes@unicamp.br).

motivation and facilitate knowledge retention. Although the literature acknowledges their benefits, there is a need to investigate how to optimize the design of these games to maximize their educational effectiveness.

A. Digital Games in Education

Digital games have proven to be practical tools for teaching and learning, providing an interactive and engaging learning environment that can increase student motivation and facilitate knowledge retention [14], [15]. The use of online games in language learning is becoming more popular, with students showing greater interest in learning and practicing the language through these games, making learning more engaging and effective [7]. These games help develop essential listening, speaking, reading, and writing skills and improve students' vocabulary, making them valuable tools for language teaching [7].

Game design is crucial to educational effectiveness, significantly influencing cognitive and intrapersonal outcomes [16]. Games that include additional instruction outside the game environment are more effective [16]. Existing literature highlights various benefits of digital games in the educational context. Simulation games, for example, promote an active and collaborative learning environment where students can develop leadership skills and mutual respect [12]. In addition, regular practice through games increases student motivation and engagement, promoting more active and collaborative learning [7].

Moreover, educational games have significantly enhanced cognitive and intrapersonal skills by offering interactive and immersive learning environments [17]. Elements such as social interaction, engaging storytelling, and personalization are crucial for crafting more captivating and effective educational experiences [13]. Game-based learning can illustrate objectives, provide immediate feedback, reinforce positive performance, and simplify complex tasks, thereby fostering greater engagement and learning effectiveness [17].

To ensure long-term effectiveness, educational digital games must incorporate clear objectives and learning contexts that align with students' needs [18]. These games offer a deeper conceptual understanding and the meaningful application of knowledge by effectively managing cognitive load—reducing extrinsic and intrinsic load while increasing germane load to optimize working memory [14].

For example, educational games facilitate understanding of complex concepts in teaching English, increase student interest and engagement, and provide an interactive and motivating learning environment, reducing the dropout rate and improving knowledge retention [19]. In addition, using game-based learning methods is especially beneficial for young learners, promoting an engaging and effective learning environment [15]. Therefore, using educational digital games as pedagogical tools improves academic performance and promotes creativity, critical thinking, and collaborative skills among students.

B. Competition and Collaboration in Educational Games

Digital games in education introduce competition that improves critical skills and encourages active participation, aligning competitive aspects with educational goals to keep the focus on learning outcomes [20]. Creating a constructive, competitive atmosphere maximizes educational benefits and reduces stress. The combination of competitive and collaborative elements promotes a balanced learning environment in which students feel valued and motivated [21]. Personalization and adaptive learning in competitive games tailor challenges to individual abilities, maintaining engagement and facilitating sustained knowledge acquisition and more profound learning [21].

Thus, competitive digital games should promote the development of competencies and motivate students. Educators can use competition as a motivational tool by designing games that challenge players against others, themselves, or the game system, creating a dynamic educational environment [11]. Competition can be synchronous, with real-time games, or asynchronous, using leaderboards to record results [11]. Structured competition increases motivation by recognizing skills and achievements, and group challenges combine competition and collaboration, enhancing learning experiences and promoting the development of social and cognitive skills [11]. Incorporating competitive elements into digital educational games improves educational experiences and develops cognitive, social, and emotional skills. Balancing competition with educational goals and creating a supportive environment engages and motivates students, promoting meaningful and lasting learning outcomes.

C. Gale-Shapley Algorithm for Stable Pair Formation

The Gale-Shapley algorithm solves the stable pairing problem in polynomial time [1]. This algorithm guarantees that, given a set of preferences, there will always be a stable solution where no pair would rather be with another partner than the one designated by the algorithm [1]. Fenoaltea [2] analysis of the differentiation between stable and optimal solutions is crucial to discuss how the application of the SMP promotes stable pairings and can also be optimized to maximize global satisfaction, considering both stability and combinatorial optimization.

Applying the concept of stable pairings to group formation ensures that preferences are considered [22]. To adapt the Gale-Shapley algorithm to educational contexts, we incorporate similarity measures such as the Jaccard similarity coefficient, into the pair formation process. This approach compares similarity and diversity between samples, facilitating the construction of preferences for effective pairing [3]. These measures can include criteria such as shared interests, complementary skills, and similar learning objectives. Studies have shown that peer similarity can improve collaboration and educational outcomes [3], [4].

The theoretical background highlights the effectiveness and challenges of digital games in education, emphasizing the need for careful design incorporating elements of social interaction, storytelling, personalization, competition, and collaboration. The literature review suggests that integrating Gale-Shapley algorithm, adapted for educational contexts, can improve the formation of stable pairs and the effectiveness of educational games.

This research aims to address the gaps identified by adapting the algorithm to work with a list of students, incorporating similarity measures for pair formation, and evaluating the effectiveness of this approach in competitive educational contexts. Next, in the methodology section, we will detail the study's design, data collection and analysis methods, and adaptation of the Gale-Shapley algorithm to achieve these objectives.

III. Methodology

This section outlines the methodological approach employed in this study to assess the effectiveness of a modified Gale-Shapley algorithm in forming compatible student pairs for educational purposes. We structured the methodology into several key components: first, a detailed description of the algorithmic modifications and the incorporation of similarity measures; second, an overview of the digital game used as the testing environment; third, the procedures for data collection and analysis; and finally, the steps taken to ensure data anonymization and compliance with ethical standards. Together, these elements form a comprehensive framework for evaluating the impact of algorithmically formed pairs on student engagement and learning outcomes.

A. Description of the Modified Gale-Shapley Algorithm

The proposed modification to the Gale-Shapley algorithm incorporates similarity measures to calculate participant compatibility scores. Instead of using fixed preference lists, compatibility scores are calculated based on Jaccard's similarity coefficients derived from student proficiency and academic performance tests.

The Jaccard similarity coefficient is a statistical metric used to compare the similarity and diversity of sets of samples. In the context of this research, the similarity coefficient is calculated based on the results of the student's proficiency and academic performance tests. The formula used is (1):

$$J(A,B) = \left|\frac{A\cap B}{A\cup B}\right| \quad (1)$$

Where A and B are the sets of test results of two participants, the value of the coefficient varies between 0 and 1, where 0 indicates no similarity, and 1 indicates complete similarity. We selected the Jaccard similarity metric due to its effectiveness in measuring the overlap between sets, making it particularly suitable for assessing student compatibility based on academic performance. To compute the Jaccard similarity coefficient, we normalized the results of students' proficiency and academic performance tests to facilitate a fair comparison.

We modify the Gale-Shapley algorithm to work with only one list of participants, starting with all participants considered free. Each participant is offered a pair with the one with the highest similarity coefficient. The participant receiving proposals accepts the proposal with the highest similarity coefficient and rejects the others. This process continues until we pair all participants or exhaust all possible proposals. algorithm 1 details the procedure. The proposed matching model adapts the Gale-Shapley algorithm to a single list of individuals, calculating compatibility scores using metrics such as inverse Euclidean distance, Jaccard similarity, and cosine similarity. The algorithm was modified to form pairs based on these scores, ensuring balanced and effective teams in educational games. Data normalization and synthetic data generation were used to test the model under various conditions, assessing execution time and pairing effectiveness.

Algorithm 1: Modified Gale-Shapley Matching with Jaccard Similarity and Random Matching

```
Input: A dataset of individuals D, Compatibility Jaccard Similarity j
Output: A set of pairs: rm_pairs, gs_pairs
  Divide dataset D into two subsets: subset_rm and subset_gs
  rm_pairs ← RANDOM_MATCHING(subset_rm)
  Initialize: gs_pairs ← ∅, FreePeople ← subset_gs
  for each p ∈ subset_gs do
     Preferences[p]← SORT_BY_PREFERENCE(p, subset_gs, j)
  end for
  while FreePeople ≠∅ do
     p← CHOOSE(FreePeople)
     for each preferred ∈ Preferences[p] do
        if preferred is free or prefers p over current match then
           if preferred in gs_pairs then
              ADD_TO_FREE(gs_pairs[preferred])
           end if
           gs_pairs[preferred]←p
           REMOVE_FROM_FREE(p)
           break
        end if
     end for
  end while
return gs_pairs, rm_pairs
```

B. Details of the Game

This study used the 'Labirinto da Educação' game on the Educapes[1] portal. We chose this game for its flexibility, the ability to customize English language content, and open-source nature. This digital educational game features interactive challenges and puzzles to enhance student learning.

Set in a virtual labyrinth, students navigate through it to find and solve puzzles. Each puzzle is an interactive challenge requiring the application of language skills such as reading comprehension, grammar, and vocabulary. Students receive immediate feedback on their answers and can only progress through the maze once they have the correct answer, helping them correct mistakes and better understand the content. Additionally, the puzzles vary in difficulty to keep students challenged without overwhelming them.

C. Data Collection Procedures

We included students enrolled in the English language course at a federal high school in Paraná, Brazil, aged between 18 and 20. The sample consisted of 20 individuals, 12 male and eight

[1] http://educapes.capes.gov.br/handle/capes/586677

female. We divided the students into two groups: an experimental group (pairs formed by the modified algorithm) and a control group (randomly formed pairs). Both groups participated in the 'Labirinto da Educação' game, where we recorded their interactions and performance. After completing the game, we administered a questionnaire to collect feedback from the students on their satisfaction, engagement, comfort, and perception of learning.

The collection instruments included a satisfaction questionnaire and performance data. The satisfaction questionnaire covered questions about satisfaction, learning aids, engagement, game effectiveness, puzzle difficulty, motivation, and contribution to learning. The game system automatically collected performance data, including average score, number of correct and wrong answers, and average and total time spent on the tasks.

The quantitative data was analyzed using descriptive and inferential statistics to compare the performances of the experimental and control groups. We analyzed the qualitative data from the questionnaire thematically to identify patterns and insights into the participants' experiences.

D. Data Anonymization

We guaranteed the participants' privacy by anonymizing the data according to the General Law on the Protection of Personal Data (LGPD)[2] guidelines and academic research ethics norms. We used randomly generated unique identifiers to record pairs and performance. We anonymized the data by replacing identifiable information with cryptographic codes, ensuring data security and privacy. Additionally, we did not collect sensitive data such as names, addresses, or other personal information, excluding these from the dataset from the outset.

The anonymized data was stored on secure servers with restricted access, using firewall technologies, data encryption in transit and at rest, and strict access controls. Authorized personnel had access to the data, and audit logs recorded all access and modification operations to ensure transparency and traceability.

We adopted these procedures to ensure compliance with the Brazilian LGPD, similar to the European General Data Protection Regulation (GDPR)[3]. Both regulations set standards for protecting personal data, ensuring individuals' fundamental privacy and security rights. By complying with these laws, we conducted the research ethically and legally, protecting the rights and privacy of participants at all stages.

IV. RESULTS

A. Pair Formation

The study aimed to adapt the Gale-Shapley algorithm to incorporate similarity measures that calculate compatibility scores and evaluate its effectiveness in forming stable pairs in educational and competitive contexts. Using Jaccard similarity coefficients calculated from student proficiency and academic performance tests, we compared a randomly paired control group with an experimental group matched by the modified algorithm.

Fig. 1 presents a heat map illustrating the compatibility scores among 20 students, calculated using Jaccard's similarity coefficient. Each cell on the map represents the similarity between two specific students, with values ranging from 0 (no similarity) to 1 (complete similarity).

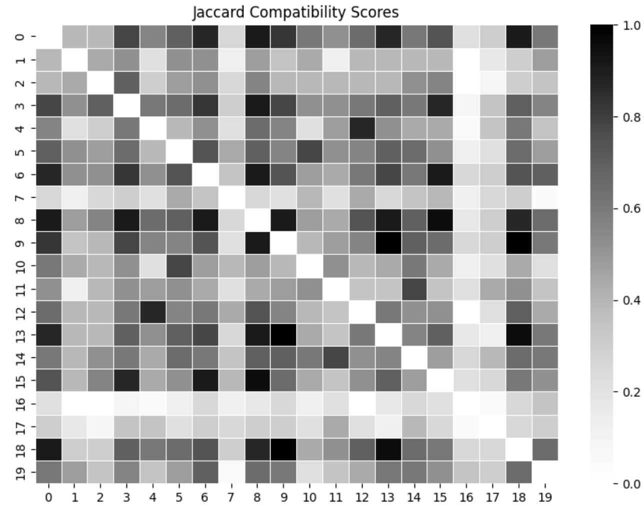

Fig. 1. Heat map of compatibility between students.

The color variations in the cells (Fig. 1) reflect different levels of compatibility: darker cells indicate greater similarity, while lighter cells indicate less similarity. This visualization helps us identify pairs of students with similar proficiency levels and academic performance, which is essential for applying the modified Gale-Shapley algorithm to form stable and effective educational pairs.

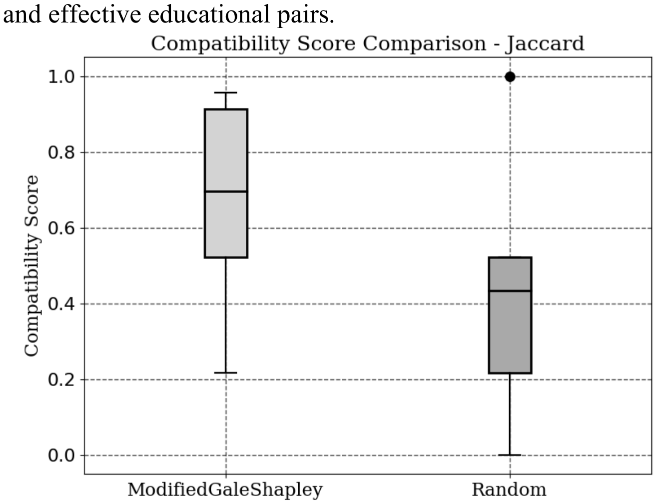

Fig. 2. Comparison of Compatibility Scores.

Fig. 2 compares the compatibility scores of the pairs of students formed by the modified Gale-Shapley algorithm and the random pairing method. Random pairing among a list of individuals uses NumPy's random module. For the pairs formed by the modified Gale-Shapley algorithm, the median compatibility score is 0.6957, with an average of 0.6609. The interquartile range (IQR) goes from 0.5217 to 0.9130, indicating the dispersion of the scores in the second and third quartiles. The minimum and maximum values are 0.2174 and 0.9565, respectively, with a standard deviation of 0.2714. As

[2] https://lgpd-brazil.info/
[3] https://gdpr-info.eu/

for the randomly formed pairs, the median compatibility score is 0.4348, with an average of 0.4348. The IQR ranges from 0.2174 to 0.5217, indicating a wider dispersion of scores compared to the modified method. The minimum and maximum values are 0.0 and 1.0, respectively, with a standard deviation of 0.3357. These results indicate that the modified Gale-Shapley algorithm tends to form pairs with greater compatibility and less dispersion in the scores, suggesting a more consistent and balanced pairing than the random method.

B. Performance Comparison

Fig. 3 shows a box plot comparing the score differences of the student pairs formed by the modified Gale-Shapley algorithm and the random pairing method.

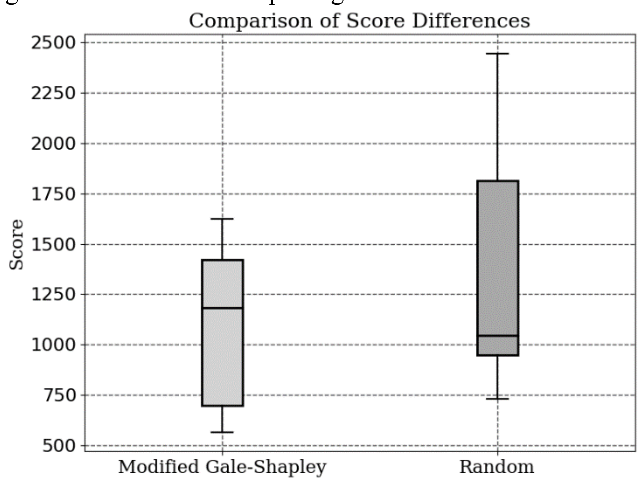

Fig. 3. Box Plot Comparison of Performance Score Differences in the Game.

The median score difference for the modified Gale-Shapley algorithm is approximately 1182, with an IQR of 698 to 1624. The minimum and maximum values are 566 and 1624, respectively. The median score difference for the randomized method is approximately 1046, with an IQR of 732 to 1814 and minimum and maximum values of 732 and 2444, respectively.

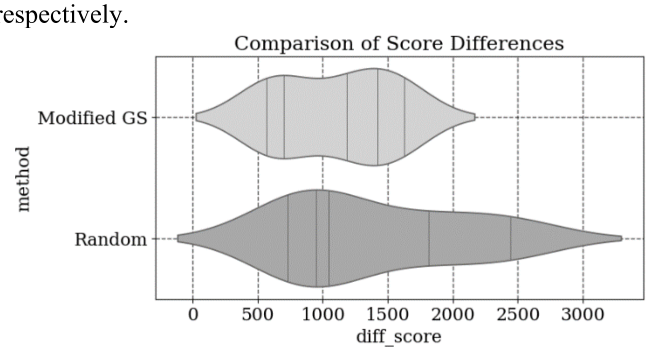

Fig. 4. Violin Plot of Comparison of Performance Score Differences in the Game.

The violin plot in Fig. 4 provides a more detailed view of the distribution of score differences, including the density of the data. For the modified Gale-Shapley algorithm, the score differences are more concentrated around the median of 1182, with a relatively symmetrical and less dispersed distribution than the random method. As for the random process, the score differences show a more dispersed distribution, with more significant variability and two prominent density peaks around 948 and 2444, indicating more significant variation in the score differences. These results suggest that the modified Gale-Shapley algorithm tends to produce pairs with smaller and less dispersed score differences, promoting greater consistency in the performance of the pairs formed. In contrast, the random method reveals more significant variability in the score differences, suggesting greater inconsistency in the performance of the pairs.

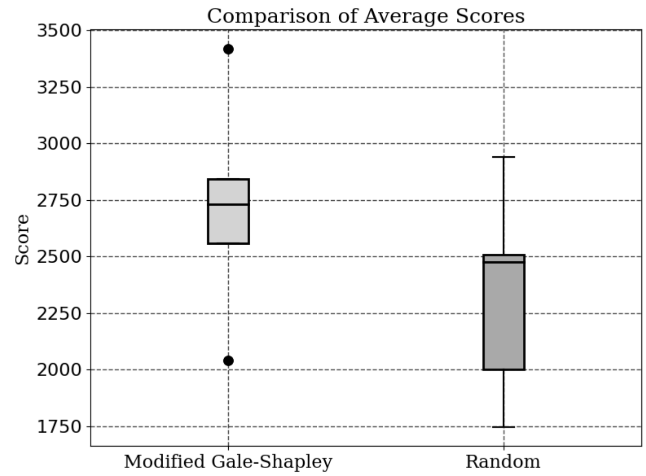

Fig. 5. Box Plot Comparison of Average Game Performance Scores.

Fig. 5 reveals that the median average score for the modified Gale-Shapley algorithm is approximately 2730, with an IQR varying from around 2557 to 2843. The minimum and maximum values are 2040 and 3419, respectively. In comparison, the median average score for the random method is approximately 2474, with an IQR of around 2003 to 2938. The minimum and maximum values for the randomized method are 1746 and 2938, respectively.

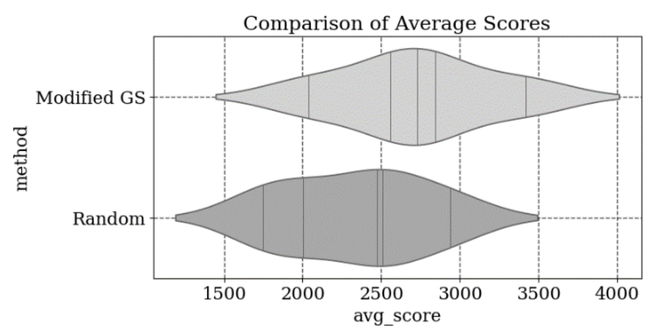

Fig. 6. Violin Plot of Comparison of Performance Score Averages in the Game.

Fig. 6 illustrates the distribution of score averages, including data density. For the modified Gale-Shapley algorithm, the score averages are more concentrated around the median of 2730, presenting a relatively symmetrical and less dispersed distribution than the random method. On the other hand, the average scores from the random method show a more dispersed distribution with more significant variability. Two prominent density peaks around 2474 and 2938 indicate a more significant variation in the average scores. These results suggest that the modified Gale-Shapley algorithm produced pairs with higher and less dispersed score averages, promoting greater consistency in the performance of the pairs formed. In contrast, the random method reveals more significant variability in the average scores, suggesting greater inconsistency in the performance of the pairs.

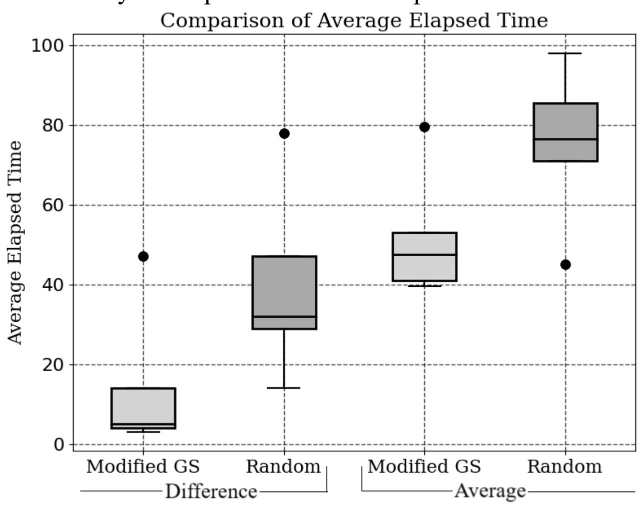

Fig. 7. Box Plot Comparison of Average Time per Response in the Game.

In Fig. 7, the box plot compares the average time per correct answer within the game for the modified Gale-Shapley algorithm and the randomized method. The modified algorithm's average time per answer varies from approximately 14 to 79.5 seconds, with a median of around 41 seconds and an IQR of between 39.5 and 53 seconds. In comparison, the random method's average response time varies from approximately 14 to 98 seconds, with a median of around 76.5 seconds and an IQR of 45 to 85.5 seconds. The outliers indicate significant variability in response times within the methods, with the modified algorithm showing more consistent and shorter times. In comparison, the randomized method shows more excellent dispersion and higher times.

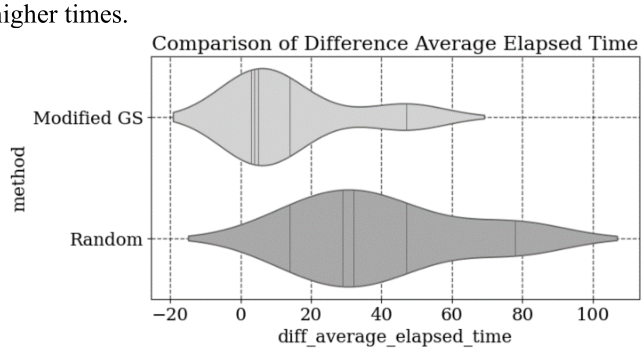

Fig. 8. Violin Plot Comparing the Difference in Average Time per Response in the Game.

Fig. 8 illustrates the distribution of the differences in the average response time, including the data density. For the modified Gale-Shapley algorithm, the differences in average response time are more concentrated around lower values, with a relatively symmetrical and less dispersed distribution compared to the random method. On the other hand, the differences in average time per response for the randomized method show a broader and more dispersed distribution with greater variability. These results suggest that the modified Gale-Shapley algorithm produces pairs with more balanced and consistent response times. In contrast, the random method reveals more significant variability in response times, suggesting less consistency in the performance of the pairs.

C. Qualitative Analysis of Student Feedback

The analysis covers various aspects including the level of engagement, perception of learning, difficulty of the challenges, motivation to solve the puzzles, and the contribution of the game format to learning.

Level of Engagement

Most students reported being 'Engaged,' with 13 individuals in this category. Three students declared themselves 'Neutral,' while another three were 'Little engaged.' Only one student reported being 'Very engaged.'

Perception of Learning

All participants stated that the game helped their learning, demonstrating an overall positive impact of the educational game.

Puzzle Difficulty

Most participants considered the puzzles 'Moderate', totaling 16 responses. Two individuals found the puzzles 'Very easy', and two considered them 'Easy'.

Motivation for Solving the Challenges

Most students (16) felt motivated to solve the game's challenges. Four students felt they needed more motivation, which may indicate the need for adjustments to maintain the interest of all players.

Contribution of the Format to Learning

Most participants (18) felt that the game format contributed to learning. Two participants did not feel this contribution, which may indicate individual preferences or limitations in the game's design.

Evaluation of the Dynamics and the Educational Game

Overall, the assessment of the game's impact on learning was primarily positive: Five students gave it the maximum score of '5 (Excellent)'. Ten participants rated it '4 (Good)'. Five students gave more neutral marks, with '3 (Neutral)'.

The analysis shows that the educational game was well received by the majority of students, with emphasis on the learning promoted and the engagement generated. However, further enhancements are necessary, particularly in sustaining student motivation and fine-tuning the puzzle difficulty to better accommodate the diverse abilities and preferences of students.

This data suggests that the game has good potential as an educational tool, but fine-tuning could further increase its effectiveness and engagement. Continuing to collect feedback and adapting the content according to the student's needs will be critical to the educational game's continued success.

D. Interpretation of Results

The quantitative analysis of participants revealed that the modified algorithm showed a range of mean scores from 2040 to 3419, with a mean of 2717.8 and a mean standard deviation of 549. In contrast, the random pairing showed a range from

1746 to 2938, a mean of 2333.6, and a mean standard deviation of 698.4. Regarding score difference, the modified algorithm ranged from 566 to 1624, while the random pairing ranged from 732 to 2444. The standard deviation of the score was 283 to 812 for the modified algorithm and 366 to 1222 for the random pairing.

In the comparative analysis, we observed that the modified method produced a higher average score (2717.8) than the random method (2333.6), with a lower standard deviation, indicating greater consistency in the results. However, the count of wrong answers was higher with the modified method but showed less variation, indicating that although students attempted more answers, they maintained accuracy. The average response time was lower for the modified method (52.7 seconds) than the randomized method (75.2 seconds), suggesting that the students paired with the modified method responded quickly. Finally, the difference in total playing time was lower for the modified method, indicating greater efficiency for the pairs formed by this method.

The interpretation of the results highlights that the modified Gale-Shapley algorithm tends to create pairs with a more balanced performance regarding correct and incorrect answers. The modified pairs showed more consistent correct answers, ranging from 32 to 56, and generally lower incorrect answers, indicating better collective performance. On the other hand, the randomized pairs showed more significant variation in correct and incorrect answers, with some pairs reaching up to 57 correct answers and others only 15, and incorrect answers varying significantly.

V. Discussion

The modified Gale-Shapley algorithm effectively creates balanced pairs in terms of academic performance. We recommend using this modified algorithm to balance performance between students, which is crucial for collaborative learning and fair competition. For future research, we suggest investigating the impact of balancing time spent on tasks and the correctness and incorrectness of answers.

A. Implications for Competitiveness and Engagement

The results suggest that using the modified Gale-Shapley algorithm for pair generation in educational digital games can improve competitiveness among participants. Consistency in performance, higher average scores, and lower standard deviation indicate that the pairs formed are more compatible and perform more evenly, which can lead to fairer and more engaging competition. Previous studies [11], [20] highlight that structured competition within educational games increases student motivation and improves learning outcomes. Our findings are consistent with this, showing that the lower variation in scores among pairs formed by the modified Gale-Shapley algorithm indicates a more balanced and competitive learning environment. We observed that well-structured competition in educational games provides adequate challenges to students, increasing their engagement. In our research, using the modified algorithm resulted in more compatible pairs and fairer competition, as evidenced by the lower dispersion of scores (Fig. 3, 4). This suggests that the healthy competition promoted by compatible pairs encourages students to try harder and become more involved in the activities.

B. Participant Satisfaction and Motivation

Educational literature suggests that satisfaction can increase student motivation and engagement [9], [10]. The fact that most students reported being engaged or very engaged during the activity suggests that balanced pairing contributes to a more motivating learning environment.

Forming balanced pairs using algorithms such as the modified Gale-Shapley can improve student collaboration and learning. The literature suggests that healthy competitiveness can increase student engagement and motivation, improving learning [23], [24]. In addition, using well-designed digital games such as the 'Labirinto da Educação,' can effectively engage students and improve learning through moderate challenges and immediate feedback [5], [6].

The results of this study show that pairs formed by the modified Gale-Shapley algorithm showed higher compatibility and more consistent performance than randomly formed pairs. Integrating the Gale-Shapley algorithm with educational technologies can create more effective and engaging learning environments, increasing compatibility and student satisfaction with their study partners and resulting in better learning outcomes. Implementing the modified Gale-Shapley algorithm in educational contexts where the formation of balanced and effective pairs is essential for the success of collaborative and competitive learning is recommended.

C. Practical Recommendations

Implementation of Pairing Algorithms

Educators can consider using the modified Gale-Shapley algorithm to form pairs in collaborative and competitive activities. This can be especially useful in classrooms where a balance of skills is crucial to the success of collaborative learning.

Practical example: in an English class, educators can use the algorithm to form pairs or groups for reading or writing projects. This ensures that students are paired with peers of similar proficiency levels, which can improve collaboration and learning.

Use of Educational Games

Digital games such as 'Labirinto da Educação' can be integrated into the curriculum to make learning more interactive and engaging. Please ensure the games you choose have immediate feedback and varying difficulty levels to keep students challenged without overwhelming them.

Practical example: during a unit on English grammar, the 'Labirinto da Educação' can reinforce concepts through challenges and puzzles that require the practical application of learned grammar rules.

Personalized Game Design

Developers should consider incorporating pairing algorithms such as Gale-Shapley into their games to improve the formation of pairs and groups. Incorporating these algorithms can increase learning effectiveness by ensuring players are compatible regarding skills and knowledge.

Practical example: a maths game could include a pairing system that uses algorithms to form teams of students with complementary skills, encouraging collaboration and mutual learning.

Feedback and Difficulty Adjustment

Educational games should provide immediate feedback and adjust the difficulty of tasks based on players' performance. Providing immediate feedback and adjusting task difficulty can motivate and engage students, promoting more effective learning.

Practical example: in a science game, the system can adjust the difficulty of puzzles and challenges based on students' previous answers, offering more challenging tasks for advanced students and additional support for those who need more help.

VI. Conclusions and Future Work

The present research demonstrates that using the modified Gale-Shapley algorithm for pairing in an educational context can improve healthy competitiveness among students, resulting in a more effective learning experience. The quantitative analysis indicates that the students paired with the modified algorithm obtained a higher average score and showed less variability in their results, suggesting more balanced and compatible pairs. In addition, the qualitative analysis reinforces these findings, with most participants expressing satisfaction with their pairings and reporting high levels of engagement and comfort during the activities.

Students paired with the modified Gale-Shapley algorithm showed greater consistency in performance and less variation in scores. This suggests pair compatibility resulted in fairer and more balanced competition, improving student engagement. For example, Fig. 3 shows that score differences between the pairs formed by the modified algorithm are smaller than those between the randomly formed pairs, indicating a more balanced competition.

The quantitative data reveals that the pairs formed by the modified algorithm performed better academically, with a higher average score and faster response time. Fig. 6 shows that the average scores of the pairs formed by the modified algorithm are more concentrated and show less dispersion, indicating greater efficiency and consistency in performance.

Future work could include investigating the impact of the pairing algorithm in different educational contexts and with larger samples may provide a better understanding of its applicability and overall effectiveness. Exploring the algorithm's use in different subjects, teaching levels, and diverse cultural environments may reveal additional insights into its flexibility and usefulness.

Carrying out longitudinal studies is crucial to investigating the algorithm's impact over a longer period. Such studies allow us to observe changes in student engagement and learning over time, helping to identify lasting effects and the sustainability of the improvements observed in the short term.

Integrating the pairing algorithm with other educational technologies maximizes the benefits of collaborative learning. Studying this integration offers insights into how the use of various technological tools together can improve the effectiveness of teaching strategies.

In summary, using the modified Gale-Shapley algorithm with well-designed digital games shows promise for improving collaborative and competitive learning. The results indicate that this approach can lead to a more balanced and practical learning experience, promoting greater student engagement and satisfaction. However, more research is needed to fully explore this approach's potential in diverse educational contexts. Expanding this study to include different populations and learning environments and integration with other educational technologies can provide a solid foundation for the generalized application of pairing algorithms in education.

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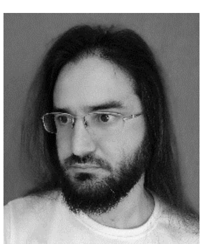
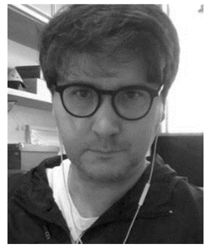
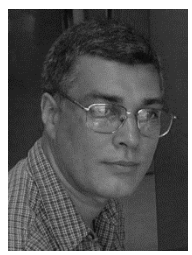


Luiz Carlos Pinheiro Junior, a professor and researcher in digital games, artificial intelligence, and education. With a degree in Digital Games Technology from the FATEC Americana and a master's degree in electrical engineering and computing from the University of Campinas (UNICAMP), he is currently pursuing his PhD in Electrical Engineering at the same university. With over 20 years of experience in the Information Technology sector, he transitioned to higher and technical education in 2019. He has taught a diverse range of subjects at institutions such as the Federal Institute of São Paulo and the Federal Institute of Paraná. His research interests revolve around the innovative use of digital games and artificial intelligence as pedagogical tools.



Everton Gomede is a computer scientist and data analyst with over 20 years of expertise developing data-driven decision-making tools. He holds a Postdoctoral and Ph.D. in Electrical Engineering/Computing from UNICAMP, a master’s in computer science from the State University of Londrina, and two MBAs from the Getulio Vargas Foundation. Currently, he is engaged in research at the University of British Columbia and the University of Guelph, focusing on data analysis for agriculture. His professional journey includes roles at prestigious institutions such as FEEC/Unicamp, USP and companies like Vanhack and Sicoob. Everton is passionate about innovation and specializes in leveraging machine learning and data science to transform complex data into actionable insights. He is also a prolific educator and author, contributing extensively to scholarly literature in data science and machine learning.



Leonardo de Souza Mendes holds a degree in Electrical Engineering from Gama Filho University (1984), a master’s degree in electrical engineering from the Pontifical Catholic University of Rio de Janeiro (1987), and a doctorate in Electrical Engineering from Syracuse University (1991). He is currently a Full Professor (MS6) at the State University of Campinas and a project reviewer for the Fundação de Amparo à Pesquisa do Estado de São Paulo. His main areas of expertise are smart cities, smart enterprises, and developing cognitive systems for smart grids. He is the Communications Networks Laboratory (LARCOM) Scientific Director at UNICAMP's School of Electrical and Computer Engineering. LARCOM has been working since 2001 on the proposal and development of Municipal Infovias (or open access metropolitan networks - OAMN), digital cities, and the current smart cities. Its main research areas are developing and applying intelligent systems for cities, with applications in education, health, and public management.