Using Provenance to Evaluate Student Learning of Biological Control in an Educational Game

Leonardo Lignani, Flávio Marques, João Quadros, Myrna Amorim,
Mario Guimarães, Eduardo Ogasawara, Joel dos Santos

***Abstract*—For several knowledge areas, experiments and practical activities are not feasible in the academic environment. In these cases, the use of computational resources becomes an alternative. Computer games are proposed as tools to improve student learning. A common challenge in this scenario is assessing whether the student is mobilizing theoretical concepts during the game. Recent studies in learning analysis describe methodologies and approaches for analyzing educational games. However, richer and deeper analyses are still little explored, especially when it comes to games with a great variety of decisions and gameplay. Using data provenance in games appears to be a great approach. It has not been much explored in the educational game environment. In this article, we present a provenance data-driven approach to assess student mobilization of concepts while playing. With data collected through provenance, we apply data mining techniques to identify player behavior profiles. An experimental evaluation with undergraduate students was performed on top of the Control Harvest game. Experiment results with our approach showed a more detailed analysis of student performance using the game provenance.**

***Index Terms*—Learning Systems, Provenance, Educational Game, Biology, Biological Control.**

I. INTRODUCTION

CONSIDER the scenario of learning Integrated Control (IC) [1] in High-School. IC is an agricultural management practice that articulates several ecology-related concepts. It controls pests that may endanger agriculture by reinforcing the natural ability of an environment through biological control (BC). It might also use chemical control to promote temporary reductions in pests population [2]. BC is still a very relevant topic. Several studies presented in recent years analyze this method in real-life problems [3]–[5]. Through BC, it is possible to: (i) introduce exotic species into the habitat to control pests; (ii) augment the population of a pest's natural controller; (iii) modify limiting factors of the pest's controller population to increase its effectiveness against the pest.

In this example, students should understand BC to know when it can be effective for IC. Topics such as ecology and evolution frequently pose these difficulties since students must mobilize knowledge related to the interaction between species and the environment. Examples such as this one are commonly benefited whenever laboratory activities are available. However, experimental approaches in these subjects are not compatible in time and space with the scholarly environment. In these cases, computational resources provide an alternative for laboratory practices [6].

Computer games have been proposed as educational tools to enhance student learning [7]–[9]. In such approaches, the subject to be studied is part of the gameplay. Learning occurs through a process of hypothesizing, probing, and reflecting upon the game environment [10]. That process is usually driven by rewards such as points, challenges, and goals achievements. A key challenge in this educational game design is to achieve a compromise between the gameplay/entertainment properties with the scientific modeling/experimentation process.

There are some BC games available [11], [12]. The challenge is measuring their aid to the teaching and learning of BC, which is frequently done through surveys and questionnaires [13]. These are usually focused on students' evaluation of the subject.

On the other hand, data-driven approaches, such as learning analytics (LA) [14], educational data mining (EDM) [15], and game analytics (GA) [13], are increasing their applicability to aid this field. Both LA and EDM focus on understanding the educational process underlying virtual learning environments. Conversely, GA is used to track in-game interactions for game designing purposes, such as finding bugs and increase engagement and monetization [13], [16].

This leads to the following research question:

> *"How to evaluate if students are mobilizing BC concepts while playing the game?"*

Our article adopts a provenance data-driven approach to evaluate if students can mobilize BC concepts. The paper presents *Control Harvest*, an educational game to help teachers presenting the IC subject. *Control Harvest* enables students to explore IC practices in a ludic way by managing farmlands where pests endanger the crop. It narrows down the vast number of techniques that compose IC by focusing on the role of predation.

Control Harvest employs a provenance approach to track in-game interactions. The idea is to enable teachers to visualize playing strategies used by students while playing the game. Those playing strategies are related to the student being able to mobilize certain concepts necessary to correctly understand the subject addressed by the game. In the case of *Control Harvest*, Integrated Control.

Manuscript received July 23, 2021; revised MONTH XX, 20YY. This work was supported in part by CNPq, CAPES and FAPERJ. *Corresponding author: Joel dos Santos*

The authors are with CEFET/RJ - Federal Center for Technological Education of Rio de Janeiro, Rio de Janeiro, RJ 20271-110, Brazil (e-mail: leonardo.lignani@cefet-rj.br; flavio.marques@aluno.cefet-rj.br; joao.quadros@cefet-rj.br; myrna.amorim@cefet-rj.br; eogasawara@ieee.org; jsantos@eic.cefet-rj.br).

M. Guimarães is with Saint Martin University (e-mail: mguimaraes@stmartin.edu).

The rest of this article is structured as follows. Section II presents related work. Sections III and IV discuss *Control Harvest*'s design, implementation, and provenance model. Section V presents the experimental evaluation conducted with *Control Harvest*. Finally, Section VI concludes this article and discusses future work.

II. Related Work

In this article, we present *Control Harvest* as an IC-based game with support to analyzing game learning outcomes through provenance. This section, therefore, presents works related to LA on serious games and game provenance.

We conducted a systematic mapping study using the search expression string *("learning analytics"* $\vee$ *"provenance"* $\vee$ *"game analytics")* $\wedge$ *("serious game"* $\vee$ *"educational game")*. The query was run in Scopus in June 2021 and was limited to English. Query result brought 191 references. Additionally, two broader studies were added using snowballing search.

When it comes to game analysis for educational games, to standardize in-game interaction tracking for educational games, Serrano-Laguna et al. [13] presents a review of 14 out of 120 educational games found in the literature that use tracked data for learning evaluation. As a result, the authors found that in-game tracking is performed in an event-based fashion. Moreover, those games derive the following metrics from tracked data: *(i)* task completion percentage, *(ii)* time spent and rightness ratio in multiple-choice scenarios, and *(iii)* learning outcome calculated from the game score together with the other metrics.

The search for systematization of game learning analysis is also the focus of Alonso-Fernandez et al. [17]. According to the authors, the use of simple metrics does not provide information about the learning process. It uses the concept of Game Learning Analytics (GLA), which combines the educational objectives of LA with technologies that are common in GA. The authors present a two-step architecture for systematizing LA. It includes standardizing the Educational Games-specific Experience API for tracking and collecting game data and a set of visualizations for analyzing this data.

Assessing progress and learning in the use of educational games is one of the challenges faced by teachers. Interpreting game-generated data generally requires a high level of computing skills. Gomez et al. [18] propose an interactive and intuitive data visualization tool seeking to solve this problem. It shows two analysis: verifying the sequences of actions performed by students and verifying the most common mistakes made. The work was carried out on top of the game Shadowspect, which aims to present geometry content and other behavioral and cognitive constructs. The visualization tool was developed using Shiny's R framework. Through it, teachers can visualize the players' actions through icons representing the forms and events of manipulation that a student can perform in the game.

The use of data mining to improve learning assessment in educational games is presented in Alonso-Fernandez et al. [19]. This work presents a case study that seeks to measure the knowledge of students after playing, based on data collected from interactions in the game and using predictive models on top of this data. Data was collected using the Experience API. Two questionnaires were used (a pre-test and a post-test) to compare learning. The post-test questionnaire result is the target variable used for the prediction models. Two prediction models were created: a linear model to predict the exact score and a classification model to predict pass or fail. The results found in this work show that the prediction models were able to predict student learning. However, the fact that the game is based on multiple-choice questions contributes to this result.

An educational game with a greater variety of decisions and gameplay becomes more challenging to analyze the game flow. These implications of combining LA and serious games have been addressed in Hauge et al. [20]. According to this work, high performance in a game does not necessarily reflect learning. While the game induces a performance-seeking attitude, whether reaching milestones or high scores, learning requires moments of reflection, informed repetition, and breaks. The more freedom of action the game has, the greater the contrast between performance and learning. Thus, instead of analyzing only game performance, a good approach would be to analyze players' behavior throughout the game.

Meanwhile, the use of provenance in games is presented in Kohwalter et al. [16]. According to the authors, provenance differ from GA, by tracking the causal dependencies among in-game interactions and evaluating playing strategies and the causes behind a game outcome. They present a game where the player manages a software development team. Analyzing the provenance graph obtained from a game-play, the authors can understand the steps the player took to achieve the game outcome and redesign the game. However, it is important to highlight that the analysis presented by the authors depends on visualizing and understanding the constructed provenance graph. To get around this problem, in Jacob et al. [21], an approach was proposed to facilitate the understanding of the game flow and to make faster and more punctual decisions through visual representations of the data.

Kohwalter et al. [22] analyze whether provenance is more efficient and effective in identifying cause-and-effect relationships when analyzing a game session. For this evaluation, students were presented with a replay of a session of the educational game. After watching the replay, the students were divided into two groups: one with and one without provenance analysis. Finally, both groups answered a questionnaire about the events that took place within the game session. The results showed that provenance led to faster and more accurate answers [22].

Melo et al. [23] present an approach to identify player profiles based on game provenance data using clustering algorithms. Identified groups were classified according to common behavior and statistics among players. The proposed approach enabled identifying players' profile to help understand the strategies used.

Although the use of provenance enables the authors to evaluate playing strategies, it is performed with the sole intention of redesigning the game. *Control Harvest* was conceived to provide such analysis for evaluating student learning. Thus the game tracks in-game interactions following a provenance-driven approach. This means that causal relationships among player actions are analyzed to present playing strategies used throughout the game. Besides presenting the playing strategies *Control Harvest* also enables analyzing how they change or persist in deriving learning outcomes. To the best of the authors' knowledge, *Control Harvest* is the first to use a provenance-driven approach along with data mining techniques to analyze the mobilization of theoretical concepts within an educational game.

III. Control Harvest

Control Harvest is a game that uses a simplified scenario for managing an agricultural farm, presenting BC as an alternative for pest management. The game narrows the BC concept by focusing on the role of predation in BC. Figure 1 depicts the concepts addressed in the game. The left-hand side presents the thematic areas, and the right-hand side the fundamental concepts inside those thematic areas that the game approaches.

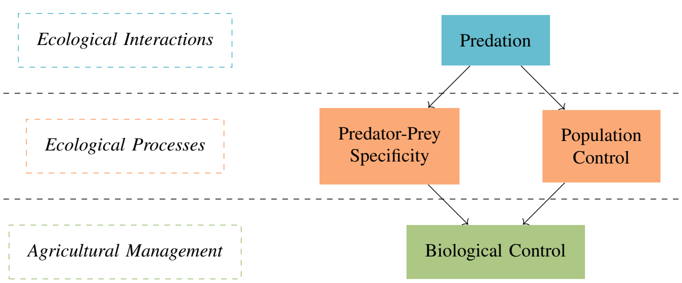


Fig. 1: Relation among the concepts addressed in *Control Harvest*.

For a correct comprehension of BC, a student must articulate concepts like "predator-prey specificity", "population control" and "biological control". *Control Harvest* enables students to mobilize those concepts by introducing or removing two predator species into the farmland. The game is designed so students may observe the effects of introducing a new species in an ecosystem on population control in viable response time.

Throughout the game, the player earns money by selling his crops and spend money buying seeds or performing pest control. The player has four plant options to cultivate: tomato, kale, grass, and corn. Each plant has different purchase and sale values. Four species of pests shall migrate to the farm: aphid, leafhopper, cricket, and caterpillar. Each pest feeds on a specific type of plant, as depicted in Figure 2. Pest control is done by inserting new predator species in the farm, following a practice of BC. Figure 2 also presents the two available predators (beetle and ladybug) and the insect species they prey on.

A. Game Interface

Control Harvest starts by asking the player name, which is used for ranking purposes and provenance as discussed in Section IV. Ranking and tutorials may be accessed from the initial screen, besides choosing the game language (English or Portuguese).

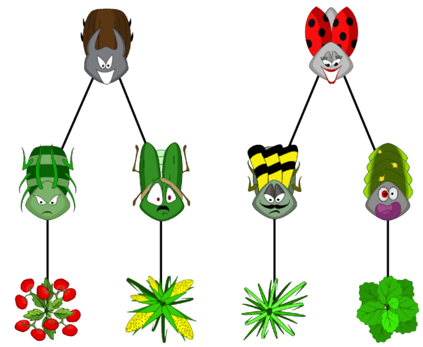


Fig. 2: Control Harvest food chain. It presents the two predators (beetle and ladybug), the fours pest species (aphid, cricket, leafhopper, and caterpillar), and the four plant species (tomato, corn, grass, and kale).

Fig. 3: Control Harvest game screen. It presents all the plants, pests, and predators in the farm area and, at the bottom, the buttons the player uses to control the game.

Figure 3 presents the game screen. Numbers 1 to 20 help identify the elements presented in *Control Harvest*. As seen in Figure 2, objects 1 to 4 are the pests, 5 and 6 the predators, and 7 to 10 are the plants. Object 11 is an indication of where the player sews. After a few seconds, the plant develops into an object corresponding to the type of plant selected by the player.

Buttons 12 to 20 are located in a menu bar and enable the player to interact with the game. Using buttons 12 to 15, the player buys seeds and can plant by clicking on the farm area. Those buttons are only available if the player has enough money. Button 16, followed by clicking on a plant, harvests a mature plant. When the harvest is complete, the player earns the sale value of the corresponding plant.

Buttons 17 and 18, followed by clicking on the farm area, inserts a predator. Button 19 removes a predator. Both operations cost money. Finally, button 20 accesses the game menu. In that menu, the player can enable/disable the sound; view a population graph; view the purchase/sales values of plants and predators, and quit the game.

B. Game Design

In *Control Harvest*, each insect (pest or predator) has an energy attribute that decrements as time passes. As the insect energy decreases, its movement becomes slower, and whenever it reaches zero, the insect dies. The insect energy is recovered whenever it feeds.

Insects move around the farm area at random. It is performed by choosing a random angle (in an interval from -15^o to 15^o) to turn every game cycle. To reinforce predator-prey specificity, insects have a field of view. If their prey is seen, they have a higher probability of turning in their direction to chase them. Predation then occurs when both insects (or insect and plant) collide. When predation occurs, a scape probability is modeled by considering the predator's predation rate and both insects' energy values. The idea is that insects with more energy are more likely to prey/escape.

Whenever insects of the same species collide, they may reproduce according to the species reproduction rate. When reproduction occurs, the insects lose an amount of energy. The population control concept is reinforced in *Control Harvest* in two ways. Players have to control *(i)* the pest population. Otherwise, they lose their crops, and *(ii)* the predator population, otherwise they receive fines. This fine is intended to present to the player a possible negative outcome of BC, *i.e.* when predator population gets out of control.

Finally, the software presents regularly to players short-term goals to keep them interacting with the game. They are presented if the player does not plant for 30 seconds or every $1,000$ points earned. Those goals demand the player to harvest one of the available plants. To increase the challenge and reinforce the predation interaction between species, a migration of pests that prey on the selected plant occurs whenever a goal is set. Therefore, the player has to devise a strategy to deal with the pests.

In summary, the above game mechanics were devised to reinforce the concepts presented in Figure 1. The predation interaction between species is shown directly by the predation mechanics between species. The practice of BC is presented in the use of predators to control pests. Besides, the goals in the game reinforce it. The predator-prey specificity is easy to observe in the game. However, it is also observed when insects are chasing their food. It helps the player to understand that each species has a defined diet. Finally, to present the importance of controlling the predator population, the game issues fines for an excess of predators. Through this fine, the idea is passed that the environment does not support that species population.

IV. Provenance Model

Carata et. al [24] defines provenance as the metadata systematically collected that describes the relationships among all the elements that contributed to the existence of a piece of data. *Control Harvest* collects provenance data about the player behavior to enable the analysis of gameplay. Provenance data is modeled according to the provenance model presented in Figure 4.

The provenance model extends the PROV model [25] following the approach presented by Kohwalter et al. [16]. It defines the cause and effect relationships that occurred throughout the gameplay. The proposed model is composed

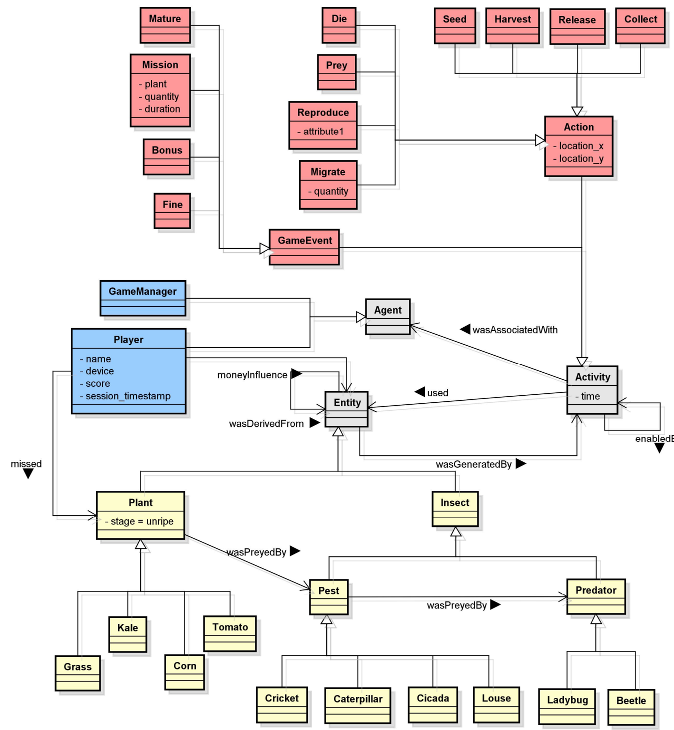


Fig. 4: Control Harvest provenance model. The model extends PROV according to the elements present in the game.

of three main parts: *(i)* agents, *(ii)* entities, *(iii)* activities. Agents represent the entities capable of carrying out actions within the game. Entities represent game objects used by the agents. Finally, activities represent the possible events that occur during the game.

In Figure 4, gray classes represent the PROV components *Agent*, *Entity*, and *Activities*. The remaining classes extend one of those three to define *Control Harvest* specific provenance classes. Agents are represented in blue, entities in yellow, and activities in red.

Control Harvest defines two agents: *GameManager* and *Player*. The first is responsible for controling the game mechanics and the second represents players themselves. Entities are divided into two main classes: *Plant* and *Insect*. The *Insect* class is further divided into two classes according to the role of the species in the game: *Pest* and *Predator*. Each of those classes (*Plant*, *Pest*, and *Predator*) is extended according to the species presented in Figure 2. Finally, there are classes that represent the existing activities in the game. Activities are divided into the classes *Action* and *GameEvent*. The first corresponds to activities performed by the *Player*, while the second corresponds to activities performed by the *GameManager*.

Classes relationships are labeled according to the influence between objects. The model provides four standard PROV relationships. The *wasAssociatedWith* indicates that an agent was involved in an activity. The *used* indicates that an entity was used in the activity. The *wasDerivedFrom* indicates that one entity was generated from another. Finally, *wasGeneratedBy* indicates that the activity generated an entity.

Moreover, it defines four new relationships. The *moneyInfluence* represents that an entity made the player gain or lose money. The *missed* represents that the player did not harvest a plant. The *wasPreyedBy* represents that an entity preyed the other. Finally, the *enabledBy* indicates that a given activity made another available.

Following the proposed model, a provenance tool was developed to store the provenance data and provide exploratory visual data analysis. The tool is composed of three main components. It includes a relational database to store game provenance data, a web service to receive the data from a device running the game and store it in the database - finally, a web page[1] to present the data visually.

V. Experimental Evaluation

The experimental evaluation[2] was conducted with 48 students from two high school classes from CEFET/RJ. During the experiment execution participants were randomly divided into four groups $G1$, $G2$, $G3$, and $G4$. The following sections present the experimental protocol (Section V-A) and the analysis of its results (Section V-B).

A. Experimental protocol

The experimental protocol was designed in three steps as depicted in Figure 5. First, students filled a pre-test questionnaire. That questionnaire was designed to gather students' previous knowledge about BC and characterize information (age, time spent studying and gaming, and previous formation). Previous knowledge is evaluated with an open question presenting the following scenario. The participant owns a rice crop with an infestation of grasshoppers. If not controlled, the participant may lose up to 80% of the planting. So he/she has to present what method he/she uses to control the pest.

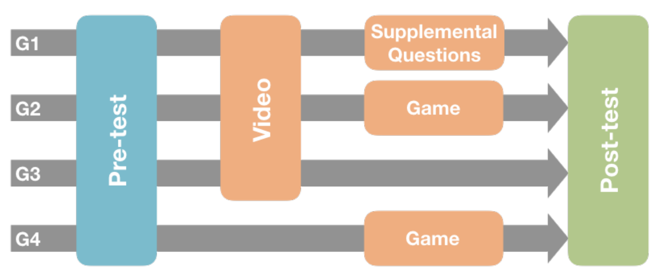


Fig. 5: Experimental protocol conducted with *Control Harvest*.

Students from groups $G1$, $G2$, $G3$ watched a video about BC at the second step. The video is a montage of three videos. The first is an agricultural TV show[3], the second and third are videos of researchers from Biological Institute[4]. The goal of the video was to mimic a classroom activity taking into account the COVID-19 pandemic context.

Students from $G1$ answered a supplementary questionnaire composed of five questions from the National High School Exam (ENEM). The idea is to simulate a traditional class scenario. After, the students proceeded to the post-test questionnaire. Students from $G2$ proceeded to play *Control Harvest* followed by a post-test questionnaire. Students from $G3$ proceeded directly to the post-test questionnaire without any supplementary activity. Finally, students from $G4$ just played *Control Harvest* (without watching the video) and proceeded to the post-test questionnaire.

The post-test questionnaire is composed of six open questions and one multi-select multiple choice question about BC. The questions are based on a deeper analysis of the rice crop scenario presented in the pre-test. The questionnaire presented that the grasshopper caused severe damages when its population reached the density of 20 individuals per rice lot. In addition, the questionnaire showed the presence of four other species of insects in different lots. The questionnaire presented an experiment isolating the grasshopper and each of the insect species. Figure 6 depicts the results observed in such an experiment.

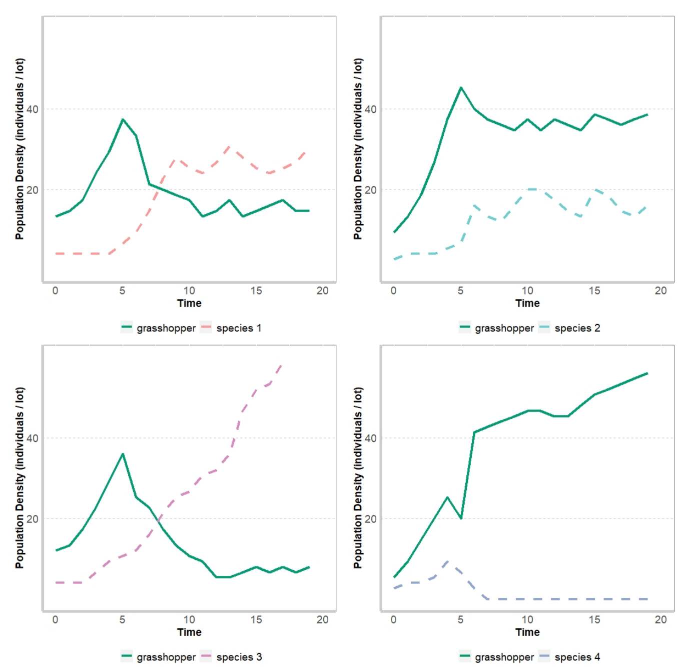


Fig. 6: Results observed in each of the creations

Besides, the questionnaire also presents the result obtained by a neighbor farm where three pesticide applications were performed to control the grasshopper population. It is depicted in Figure 7. Each blue vertical line corresponds to a moment of pesticide application.

From the described scenario, the post-test questionnaire poses two main questions and five derived ones. The first question ($TQ1$) asks the participant to select which species could be used for managing the grasshopper population. Derived questions ask about the interaction observed in each graph in Figure 6 and the usefulness of the results for agriculture.

[1] Examples of data visualization created from gameplay logs can be viewed at https://achernar.eic.cefet-rj.br/controlharvest/dashboard/session-ieeetlt2021.php. Reviewers are welcome to test the visualization seeing their respective provenance data by playing the game using the user name `IEEETLT2021`.

[2] All the information about the experiment is available at https://eic.cefet-rj.br/~gpmm/ieee-tlt2021/.

[3] Globo Rural, from Globo Television Network https://g1.globo.com/economia/agronegocios/globo-rural/

[4] http://www.biologico.sp.gov.br

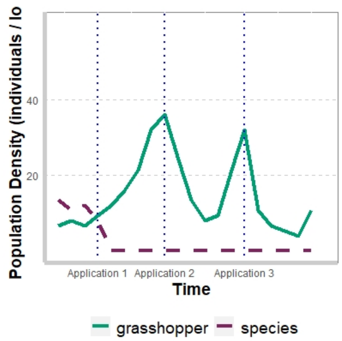


Fig. 7: Result of the pesticide application scenario.

The second question ($TQ2$) asks the participant to explain the difference observed between the type of control adopted in the neighbor farm and what would be expected in the adoption of biological control.

Questions $TQ1$ and $TQ2$ test the hypotheses that one could observe biological control principles better when playing *Control Harvest*. The hypotheses are described as follows:

- H1 The student observes that the selected species has to control the target population. Also, its population should not get out of control ($TQ1$).
- H2 The student observes the long-term effects of biological control compared to pesticide use ($TQ2$).

The division of participants into four groups was designed to enable comparing students' performance between those who played *Control Harvest* ($G2$) with those in a traditional class scenario ($G1$). We use $G3$ as a baseline to disregard the effect of repetition in our experiment. Especially since both $G1$ and $G2$ were exposed to a supplementary activity. Finally, $G4$ indicates *Control Harvest*'s ability to convey the concepts related to BC.

Besides the comparison above, this protocol aims to investigate the correlation of student answers with their strategies while playing. It is expected that students who were able to correctly identify the relationship among predators and plagues and use it for controlling the plague population would perform better on hypotheses $H1$ and $H2$.

B. Analysis of Results

Table I presents the distribution of participants per group. It also presents the number of participants in each group with previous knowledge about BC. It was considered having previous knowledge participants whose response in the pre-test questionnaire either cited directly the use of BC or something resembling it. As can be seen in the table, there is a balanced distribution between groups.

For each participant, a score was attributed to each response to questions $TQ1$ and $TQ2$. Considering hypothesis $H1$, it was expected that participants would observe that Species 1 would be the correct choice for question $TQ1$. Species 1 controls the grasshopper population, and its populations do not get out of control (upper-left graph in Figure 6). Species 3 (bottom-left) does control the grasshopper population, but its population gets out of control. Species 2 (upper-right) has no impact and species 4 (bottom-right) helps increasing the grasshopper population. Therefore, given the answers presented by the participants to question $TQ1$, Table II presents the score assigned to each answer.

TABLE I: Participant distribution per group and indication of previous knowledge.

Groups	Participants	Previous knowledge
G1	12	3
G2	12	3
G3	14	2
G4	10	2

TABLE II: Score assigned to question $TQ1$.

Choice	Score
1	1.0
1, 3	0.8
3	0.6
1, 4	0.4
1, 3, 4	0.2
2, 4	0

TABLE III: Score assigned to question $TQ2$.

Choice	Score
BC + PC	1.0
BC	0.5
PC	0.5
none	0

Question $TQ2$ aims to study hypothesis $H2$. It was expected that participants would observe that using BC has a long-term effect on the grasshopper population control as a right answer for question $TQ2$. In this case, several pesticide applications are required to control it (see Figure 7). Therefore, as seen in Table III, the score assigned to participants' answers considered identifying BC as long-term (BC) and that pesticides require several applications (PC).

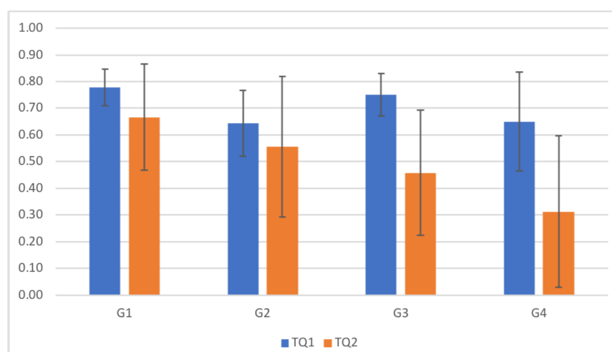
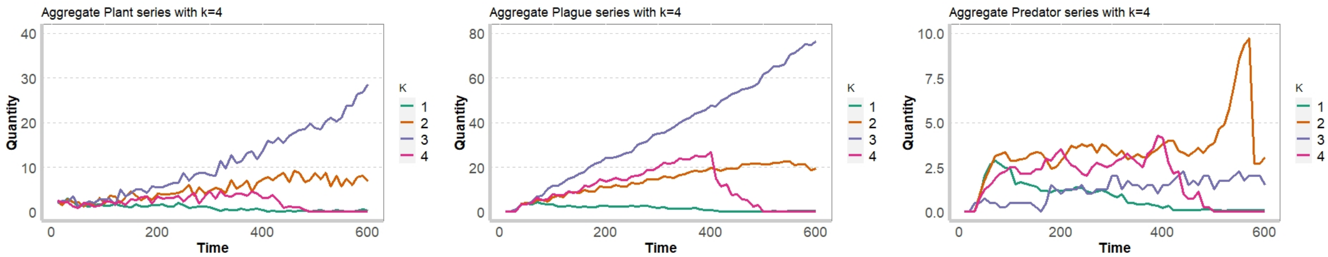


Fig. 8: Average score and 95% confidence interval per group in questions $TQ1$ and $TQ2$.

Figure 8 presents an initial analysis of the performance of each group regarding questions $TQ1$ and $TQ2$. $G4$ obtained the worst result and $G1$ the best result in both questions. $G3$ performed better than $G2$ in question $TQ1$, and worse in $TQ2$. Considering this analysis, one could say that the game failed in hypotheses 1 and 2 compared to a traditional class



(a) Average plant time series. (b) Average pest time series. (c) Average predator time series.

Fig. 9: Average population graph for plants, pests, and predators for each profile identified using the k-means method for $k = 4$.

scenario. Moreover, the class (video) had a significant impact on participants' performance.

To demystify that impression, we use the provenance data to cluster the players into those who performed better and those who performed worse in *Control Harvest*. Provided the game did help the student to mobilize the concepts presented in Section III, we expect that those who performed better in *Control Harvest* also performed better in hypotheses $H1$ and $H2$.

First, we use the provenance data acquired during the experiment to construct, for each participant in groups $G2$ and $G4$, a temporal series regarding its gameplay for the first 10 minutes of the game. That limit was chosen since it was the recommended time for participants to play the game in the second step of the experiment.

Considering playing *Control Harvest*, a successful strategy is seen when the player can keep a big crop with the pest population kept under control. A time series is built by combining plant population, pest population, and predator population graphs. These time series were grouped using the k-means method. From silhouette analysis, k was set to four. These four groups represent different player profiles. Figure 9 presents the average population graph for plants, plague, and predators for each profile.

Based on the above profiles, it is possible to identify the players who played well or poorly and later evaluate their performance in questions $TQ1$ and $TQ2$. Profile $K1$ groups all short gaming sessions related to training sessions to get used to the game interface. Profiles $K2$ and $K4$ represent good gaming sessions as the pest population is kept under control even with an increase in the plant population. It is worth noticing that both profiles used predators to control the pest population. Profile $K3$, however, represents bad gaming sessions as the pest population grows without control. It is worth noticing that this profile used fewer predators to control the pest population than $K2$ and $K4$.

Gaming statistics, presented in Table IV corroborate the previous analysis. The playing time and the number of goals launched corroborate that profile $K1$ consists primarily of training sessions. On the other hand, profile $K3$ has the lowest harvest rates and score per time. Moreover, although profiles $K2$ and $K4$ present good statistics, profile $K4$ consists mainly of participants that played either the training version or the full version for less than 10 minutes. Therefore, we can conclude that profile $K2$ represents participants who played the game well and profile $K3$ those who misplayed the game.

Finally, we present a comparative analysis of the participants' results in questions $TQ1$ and $TQ2$, subdividing group $G2$ according to the player profile. Figure 10 presents those results. As shown in the table, participants who played well ($G2K2$) now present a similar performance in question $TQ1$ and better performance in question $TQ2$ than group $G1$. Group $G2K2$ also performs better than $G3$ in both questions. In turn, participants that played poorly ($G2K3$) present the worse performance in question $TQ1$. However, for the second question, participants from the group $G2K3$ present a similar performance to $G3$.

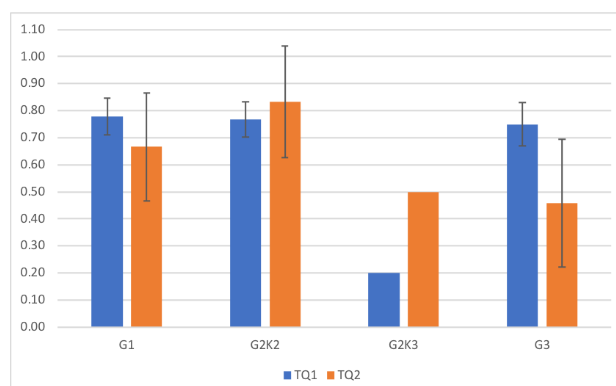


Fig. 10: Average score and 95% confidence interval per group/profile in questions $TQ1$ and $TQ2$.

The results obtained using the provenance data confirm that those who played well performed better in questions $TQ1$ and $TQ2$. *Control Harvest* acted as a way to reinforce concepts presented in class, especially the long-term effect of BC and its possible negative side effect. However, class participation is important since (just) playing the game was not enough to present a better performance than in a traditional class scenario. Moreover, it is worth highlighting the importance of using provenance data to provide a detailed analysis of participants' performance. This approach enables teachers to focus on students that did not perceive the concepts mobilized by the game to improve their learning outcome.

TABLE IV: Average gaming statistics per player profile.

Profile	**Gaming Time *(s)***	**Predator fines**	**Goal lauched**	**Score/time**	**% of plants harvested**	**% of goals accomplished**
K1	250.84	1.77	0.74	5.84	0.82	0.12
K2	1127.29	13.93	4.79	8.84	0.86	0.5
K3	972.25	0.75	2.00	2.32	0.58	0.25
K4	435.50	2.13	1.13	6.09	0.90	0.2

VI. Conclusion

The results of our experimental evaluation suggest that the provenance-driven approach combined with the use of data mining can provide a more detailed analysis of student performance. An analysis without considering the provenance data may lead to incomplete conclusions. In turn, through the analysis of the data of origin, it is possible to visualize the strategies adopted by each one of the players. Collecting data by provenance provides a significant advantage, especially in games with various choices and gameplay.

The use of data mining has been shown to assist in the analysis of provenance data. Through its use, it was possible to draw four profiles of players present in the experimental evaluation, namely: (i) training sessions, (ii) participants who played the game well, (iii) participants who misplayed the game, and (iv) participants who played for less than ten minutes. With these profiles, it was possible to quickly separate the sessions and carry out a specific analysis for each of the groups. This type of analysis allowed us to discover that participants who performed well in the game also had better results in the post-test questionnaire. These results allow teachers to identify students with more difficulties in mobilizing the concepts presented in class through their gameplay profiles.

For future work, we believe that the inclusion of the results found through mining directly within the visualization tool would be of great value to facilitate this approach by educators. Another aspect to be improved is the systematization of the tool to facilitate its application in different educational games. With tool systematization and data mining metrics, it will not require a high level of computer skills from teachers.

Acknowledgments

The authors would like to thank CNPq, CAPES, and FAPERJ for partially funding this research.

References

[1] V. Stern, R. Smith, R. Van den Bosch, K. Hagen, and others, “The integration of chemical and biological control of the spotted alfalfa aphid: the integrated control concept,” *Hilgardia*, vol. 29, no. 2, pp. 81–101, 1959.

[2] J. Handelsman and E. Stabb, “Biocontrol of soilborne plant pathogens,” *Plant Cell*, vol. 8, no. 10, pp. 1855–1869, 1996.

[3] D. Mansour, M. Pérez-Hedo, J. Catalán Estellés, F. Karamaouna, M. Braham, J. Jacas, and A. Urbaneja, “Biological control of the citrus leafminer 25 years after its introduction in the valencia citrus growing area (spain): A new player in the game,” *Biological Control*, vol. 155, p. 104529, 01 2021.

[4] A. Bell, W. Zhang, and K. Nou, “Pesticide use and cooperative management of natural enemy habitat in a framed field experiment,” *Agricultural Systems*, vol. 143, pp. 1–13, 03 2016.

[5] G. Alvarez-Baz, M. Fernandez-Bravo, J. Pajares, and E. Quesada-Moraga, “Potential of native beauveria pseudobassiana strain for biological control of pine wood nematode vector monochamus galloprovincialis,” *Journal of invertebrate pathology*, vol. 132, 08 2015.

[6] J. Cardoso, D. Caetano, R. Abreu, J. Quadros, J. Santos, E. Ogasawara, and L. Lignani, “Supporting the Learning of Evolution Theory Using an Educational Simulator,” *IEEE Transactions on Learning Technologies*, vol. 13, no. 2, pp. 417–424, 2020.

[7] J. P. Gee, *What video games have to teach us about learning and literacy*, 2nd ed. New York: St. Martin’s Griffin, Dec. 2007.

[8] D. B. Clark, E. E. Tanner-Smith, and S. S. Killingsworth, “Digital games, design, and learning: A systematic review and meta-analysis,” *Review of Educational Research*, vol. 86, no. 1, pp. 79–122, 2016.

[9] J. L. Plass, R. E. Mayer, and B. D. Homer, *Handbook of game-based learning*, 1st ed. Cambridge: Mit Press, Feb. 2020.

[10] J. Hamari, D. J. Shernoff, E. Rowe, B. Coller, J. Asbell-Clarke, and T. Edwards, “Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning,” *Computers in Human Behavior*, vol. 54, pp. 170 – 179, 2016.

[11] A. Shelton, “Parasitoids,” https://biocontrol.entomology.cornell.edu/paragame.php, Tech. Rep., 2021.

[12] ——, “Weed Feeders,” https://biocontrol.entomology.cornell.edu/weedgame.php, Tech. Rep., 2021.

[13] A. Serrano-Laguna, I. Martínez-Ortiz, J. Haag, D. Regan, A. Johnson, and B. Fernández-Manjón, “Applying standards to systematize learning analytics in serious games,” *Computer Standards and Interfaces*, vol. 50, pp. 116–123, 2017.

[14] T. Elias, “Learning analytics,” *Learning*, pp. 1–22, 2011.

[15] C. Romero and S. Ventura, “Educational Data Mining: A Review of the State of the Art,” *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 6, pp. 601–618, 2010.

[16] T. C. Kohwalter, E. G. W. Clua, and L. G. P. Murta, “Game Flux Analysis with Provenance,” in *Advances in Computer Entertainment*, D. Reidsma, H. Katayose, and A. Nijholt, Eds. Cham: Springer International Publishing, 2013, pp. 320–331.

[17] C. Alonso-Fernandez, A. Calvo-Morata, M. Freire, I. Martinez-Ortiz, and B. Fernández-Manjón, “Systematizing game learning analytics for serious games,” 04 2017.

[18] M. Gomez, J. A. Ruipérez-Valiente, P. Martínez, and Y. Kim, “Applying learning analytics to detect sequences of actions and common errors in a geometry game,” *Sensors*, vol. 21, p. 1025, 02 2021.

[19] C. Alonso-Fernandez, I. Martinez-Ortiz, R. Caballero, M. Freire, and B. Fernández-Manjón, “Predicting students’ knowledge after playing a serious game based on learning analytics data: A case study,” *Journal of Computer Assisted Learning*, vol. 36, 12 2019.

[20] J. Hauge, R. Berta, G. Fiucci, B. Fernández-Manjón, C. Padron-Napoles, W. Westra, and R. Nadolski, “Implications of learning analytics for serious game design,” *Proceedings - IEEE 14th International Conference on Advanced Learning Technologies, ICALT 2014*, pp. 230–232, 09 2014.

[21] L. Jacob, T. Kohwalter, A. Machado, and E. Clua, “A game design analytic system based on data provenance,” 10 2013.

[22] T. C. Kohwalter, E. W. G. Clua, and L. G. P. Murta, “Reinforcing software engineering learning through provenance,” in *2014 Brazilian Symposium on Software Engineering*, 2014, pp. 131–140.

[23] S. Melo, T. Kohwalter, E. Clua, A. Paes, and L. Murta, “Player behavior profiling through provenance graphs and representation learning,” 09 2020, pp. 1–11.

[24] L. Carata, S. Akoush, N. Balakrishnan, T. Bytheway, R. Sohan, M. Seltzer, and A. Hopper, “A primer on provenance,” *Commun. ACM*, vol. 57, no. 5, p. 52–60, May 2014. [Online]. Available: https://doi.org/10.1145/2596628

[25] w3.org, “PROV Model Primer W3C,” https://www.w3.org/TR/2013/NOTE-prov-primer-20130430/, Tech. Rep., 2021.