# Theoretical Foundations and Evaluations of Serious Games for Learning Data Structures and Recursion: A Review

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**Abstract.** Data structures and recursive algorithms are challenging concepts to learn because they are abstract and difficult to relate to familiar knowledge. Many researchers suggest that digital serious games may be a good tool to facilitate the learning process of these topics. This article presents a review of currently available digital serious games for learning that focus on teaching data structures and recursive algorithms. The review identifies and classifies the specific data structures and recursive algorithms covered by those games, analyzes the learning theoretical foundations for the games, and assesses the studies performed to evaluate the effectiveness of the games.

**Keywords:** Data structures · Literature review · Recursion · Serious games

## 1 Introduction

Data structures and recursive algorithms are fundamental topics in Computer Science [37]. Their proper usage ensures the good performance of a computational system. For this reason, the Association for Computing Machinery (ACM) recommends their study at an early stage of the undergraduate program [2]. However, advanced data structures and recursive algorithms are difficult topics because they are abstract and difficult to relate to familiar knowledge [3, 45]. Therefore, visualization tools have been created to facilitate the learning process. However, studies show that visualization tools do not increase learning gains due to the fact that students engage passively with such instruments [21]. For this reason, many researchers suggest that digital serious games may be useful for facilitating learning of data structures and recursive algorithms, because serious games allow students to visualize the data structure in an active way.

The aim of this article is to review the state of the art of digital serious games for learning that teach data structures and recursive algorithms. Specifically, this review aims to: (1) identify which serious games for learning focus on data structures and recursive algorithms, (2) identify and classify the specific data structures and recursive algorithms covered by those games, (3) analyze the learning theoretical foundations for the games, and (4) assess the studies performed to evaluate the effectiveness of each game.


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# 2 Methodology

This review follows the guidelines suggested by Kitchenham and Charters [26] for carrying out systemic literature reviews in computer science, which were later adapted by Calderón and Ruiz [6] and Petri and von Wangenheim [33] for reviewing serious games. The following sections describe the review objectives and protocol.

## 2.1 Research Questions

The research questions (RQ) covered by this review are:

- Topic
  - RQ1. What are the data structures or recursive algorithms covered by the reviewed digital serious games?
- Theoretical foundations
  - RQ2. What are the learning theories or approaches used by the digital serious games to ensure learning?
  - RQ3. Which types of cognitive processes are required to achieve the digital serious games learning objectives?
  - RQ4. Which dimensions of knowledge are supported by the digital serious games?
- Evaluation aspects
  - RQ5. Which factors are evaluated during the experiments?
  - RQ6. Which experimental design is used to evaluate the digital serious games?
  - RQ7. Which data collection tools are used in the study?
  - RQ8. Which data analysis methods are used to analyze the data?

## 2.2 Inclusion and Exclusion Criteria

For this review, we included articles that reported on one or more digital serious games that cover data structures and recursion topics. Specifically, we focused on articles written in English, available via digital libraries and published between 1999 and 2019. We did not include articles that report on gamification or non-digital serious games. However, articles lacking information to answer all the research questions were included as long as they could answer some of the questions. Additionally, we assessed the quality of the reviewed articles; we only considered articles published in peer-reviewed journals and conference proceedings. Finally, articles not clearly written or possessing serious methodological problems were excluded.

### 2.3 Extracted Data and Classification Criteria

To answer the RQs, we developed guidelines to extract and classify the articles' data as enumerated in the following list.

1. **Covered topic**. The covered topic consisted of the name of the data structure or recursive algorithm covered by the game. Data structures were presented without classification in order to be as comprehensive as possible. Finally, recursive algorithms were aggregated and presented under a category named "recursive algorithm."
2. **Learning theory or principle**. For each article, the learning theory or principle that the digital serious games used to facilitate learning was extracted. Learning theories were defined as theories that explain how humans learn (e.g., Situated Learning [28] or Kolb's Experiential Learning Theory [27]). Learning principles were defined as constructs, concepts, methodologies, or processes that facilitate learning (e.g., scaffolding [49], or learning by analogies and metaphors [15]). We only extracted the learning theory/principle if it was reported in the article.
3. **Cognitive process and knowledge dimension**. To classify the cognitive processes that a player must apply to achieve the learning objective and dimension of knowledge delivered by the game, Bloom's revised taxonomy framework [1] was used. According to [1], there are six cognitive process: *remember*, *understand*, *apply*, *analyze*, *evaluate*, and *create*. Additionally, there are four dimensions of knowledge: *factual*, *conceptual*, *procedural*, and *metacognitive* [1]. Usually, the cognitive processes and knowledge dimensions of a learning tool should be reported in the learning objectives section [4]. However, if an article did not mention them explicitly, we deduced these aspects from the game description, paying attention to the actions (verbs) that the player must perform while playing the game (the learning activities).
4. **Evaluated factors**. Evaluated factors commonly assess the users' behaviors or opinions about the game. To classify these factors, we used the factor classification framework suggested by Petri and von Wangenheim [33]. The framework has ten categories: learning, motivation, user experience (UX), usefulness, usability, instructional aspects, correctness, completeness, quality, and 7S-model features. Some articles do not explicitly report the evaluated factor. In those cases, we deduced the factors from the article's description of the data collection instruments.
5. **Research design**. Research designs were classified using the classification framework suggested by [33]. This framework divides experimental designs into four categories: *ad-hoc*, *non-experimental*, *quasi-experimental*, and *experimental*. The ad-hoc category includes designs that analyze "learner's informal comments after they played the game or describing some observations of pilot studies" [33]. The *non-experimental* category consists of systematically defined evaluations that do not follow a strict experimental design. Experimental designs use random assignment to allocate the participants in either the treatment or the control group. In contrast, quasi-experimental designs do not employ the random assignment approach.
6. **Instrument**. Data collection tools used in the game evaluations, such as qualitative surveys, tests/questionnaires, interviews, and observations were extracted from the selected articles.

7. **Data analysis methods**. The name of the analysis methods and type of method (quantitative or qualitative) were extracted from each article. Quantitative methods used were classified as either descriptive or inferential statistics.

### 2.4 Search Strategy

Digital libraries reviewed included ACM Digital Library, IEEE Xplore, SpringerLink, SAGE Journals, ScienceDirect, and Scopus. We selected these data sources because they have great influence in the Computer Science domain. Furthermore, we searched for additional related articles using Google Scholar to consider studies indexed on different journals outside of the mentioned databases.

For each data source, we defined a search string using core concepts and their synonyms. The following key words were used for the construction of each string: *educational games*, *serious game*s, *game-based learning*, *data structures*, *recursion*, and *sorting*.

### 2.5 Execution of the Review

We performed the systematic literature review between December 2019 and June 2020. The review was executed in three stages. Table 1 shows the results (number of articles) of each stage. In the first stage, the initial search, queries were executed in all selected digital libraries and Google Scholar. After executing the queries, 9795 articles were retrieved.

**Table 1.** Number of articles reviewed and analyzed during the literature review.

| | ACM | IEEE Xplore | Springer-Link | SAGE | Elsevier | Scopus | Google Scholar | Total |
|---|---|---|---|---|---|---|---|---|
| Stage 1. Initial Search | 23 | 32 | 1053 | 65 | 594 | 78 | 7950 | 9795 |
| Stage 2. Brief analysis | 23 | 32 | 1053 | 65 | 594 | 78 | 350 | 2195 |
| Stage 3. Complete analysis | 5 | 15 | 1 | 0 | 0 | 3 | 7 | 31 |
| Final selection | 4 | 11 | 1 | 0 | 0 | 1 | 2 | 19 |

In the second stage, the title of each article retrieved from the digital journals (including the 350 most relevant articles pulled from Google Scholar) were read. In total, this led to us reviewing 2195 articles in the second stage. When the title did not provide enough information to exclude or include the article, we proceeded to read the article's abstract.

All repeated articles were excluded. At the end of the second stage, 31 promising articles were identified.

In the third stage, we proceeded to read the whole article and to extract the data. During this stage, some articles were excluded due to the following reasons: some were not digital games, others were not legibly written, and others were about gamifications or visualization tools. At the end of this stage, we found nineteen articles reporting data on fifteen serious games and two bundles of mini games designed to teach data structures and recursion.

## 3 Results and Analysis

### 3.1 Topic

With regard to RQ1, we identified nine data structures (array, 2D array, stack, queue, linked list, dictionary, tree, binary tree and the Adelson-Velsky and Landis tree) and six recursive algorithms (Hanoi Tower recursive algorithm, tree traversal, binary search, deep-first search, Fibonacci and Factorial). Eight digital serious games were found to focus on a single data structure or algorithm while seven games were found to cover more than one topic. Regarding the bundles, each mini game was found to focus on a single data structure or algorithm. Table 2 summarizes information extracted from the articles regarding data structures and recursive algorithms covered in each digital serious game or bundle. In the table, the name, associated reference, and data structures or algorithms for each game are presented. As mentioned above, all recursion algorithms were aggregated in a single column. A grey box with an "X" indicates the primary topic covered, while a white box with an "X" indicates a secondary topic by a game.

### 3.2 Theoretical Foundations

In relation to the learning theories and principles (RQ2), eleven games/bundles (65% of the reviewed games) reported one or more learning theories or principles that support learning while playing the game. In total, we found eleven theories/principles: immediate feedback [19], Pink's Motivation Theory [34], gamification [11], intrinsic motivation [41], motivation [41], analogies and metaphors [15], productive failure [25], learning by doing [5], the Flow [10], scaffolding [49] and constructionism [20]. Constructionism theories and principles were the most widely used (nine of seventeen). The second column in Table 4 lists the learning theories/principles used by each game.

Concerning cognitive processes (RQ3), only *Stack Game* was found to explicitly report this aspect. Consequently, we deduced the cognitive processes of the rest of the games based on the descriptions in the articles. It was found that in fourteen of the seventeen games, players must employ the *apply* cognitive process. Additionally, we found that in four of the five minigames of the *DSLEP Bundle* as well as *Star Chef*, *Stacks and Queues*, and *Ramle's Stack Game*, players must employ the *remember* cognitive process. These games are simpler and therefore only require players to remember facts about the relevant data structure or algorithm (e.g., the stack follows the last-in-first-out principle) in order to solve game challenges. In contrast, *Stack Game*, *Space Traveler* and *Elemental* include coding challenges which require players to write well-known algorithms

**Table 2.** Data structures covered by the games.

| Game | Array | 2D Array | Stack | Queue | Linked List | Dictionary | Tree | Binary Tree | AVL Tree | Recursion*** |
|---|---|---|---|---|---|---|---|---|---|---|
| Wu's Castle [16, 17] | X | X | | | | | | | | |
| Star Chef [30] | | | X | | | | | | | |
| Stacks and Queues [32] | | | X | X | | | | | | |
| Stack Em Up [22] | | | X | | | | | | | |
| Stack Game [13, 14] | | | X | | | | | | | |
| Ramle's Stack Game [36] | | | X | | | | | | | |
| Space Traveller [47] | | | | | X | | | | | |
| La Petite Fee Cosmo [24] | | | | | X | | | | | |
| Mario [43] | | | | | | | | X | X | |
| AVL Tree Game [40] | | | | | | | | | X | |
| Elemental [7] | | | | | | | | X | | X |
| HTML5 Hanoi Tower [42] | | | X | | | | | | | X |
| Recursive Runner [48] | | | | | | | | | | X |
| Critical Mass [29] | | X | | | | | X | | | X |
| Resource Craft [23] | X | | | | | X | | | | |
| Prototypes Bundle* [38] | | | | | X | | | X | | X |
| DSLEP Bundle** [9] | X | | X | X | X | | | | | |

* The prototype bundle includes the following games: Binary Search Game, Singly Linked List Game, and Binary Search Tree Game.
** This bundle includes the following games: Piperray, Hanoi Tower, Asterostacks, Queue Race, and Snake Linked List.
*** The recursive algorithms are Hanoi Tower recursive algorithm, tree traversal, binary search, deep-first search, Fibonacci, and Factorial.

(e.g., depth-first-search or the linked list insert and remove algorithms). Therefore, to achieve the objectives for this set of games, players must employ the *understand*, *apply*, and *analyze* cognitive processes. Finally, *Critical Mass* and *Resource Craft* were found to involve the widest range of cognitive processes. In these advanced coding games, players are required to code a program capable of playing the game. This involves creating an original program which the player must then evaluate and optimize, taking into account the results given by the game system. Consequently, the player must use all the cognitive processes listed in Bloom's revised taxonomy.

Concerning the knowledge dimension (RQ4), results showed that fourteen games deliver procedural knowledge with only three games and four mini games of the *DSLEP Bundle* delivering factual knowledge. The challenges of these games require that the player only remember certain facts or principles of the data structure. However, some games were found to deliver both factual and conceptual knowledge. For example, in certain serious games, the game story or in-game messages provided players with conceptual and factual information that they could use to solve challenges of the game. Finally, three games were found to deliver factual, conceptual, and procedural knowledge.

Table 3 summaries the learning theories/principles, dimensions of knowledge and cognitive processes associated with each game. The term NI (not included) is used to note cases where articles did not report a learning theory or principle.

**Table 3.** Theorical foundations delivered by the games.

| Game | Learning theory or Learning approach | Dimension of knowledge[a] | Remember | Understand | Apply | Analyze | Evaluate | Create |
|---|---|---|---|---|---|---|---|---|
| Wu's Castle [16, 17] | Feedback<br>Scaffolding | P | | X | X | | | |
| Star Chef [30] | NI | F | X | | | | | |
| Stacks and Queues [32] | Constructionism | F | X | | | | | |
| Stack Em Up [22] | Constructionism<br>The Flow | F/C/P | | | X | | | |
| Stack Game [13, 14] | Constructionism<br>Learning-by-doing | F/C/P | | X | X | X | | |
| Ramle's Stack Game [36] | Scaffolding | F | X | | | | | |
| Space Traveler [47] | NI | P | | X | X | X | | |
| La Petite Fee Cosmo [24] | Productive failure | P | | | X | | | |
| Mario [43] | NI | P | | | X | | | |
| AVL Tree Game [40] | Constructivism<br>Scaffolding | P | | | X | | | |
| Elemental [7] | Scaffolding<br>Analogies & Metaphors | F/C/P | | X | X | X | | |
| HTML5 Hanoi Tower [42] | NI | P | | | X | | | |
| Recursive Runner [48] | NI | P | | | X | | | |
| Critical Mass [29] | Motivation | P | X | X | X | X | X | X |
| Resource Craft [23] | NI | P | X | X | X | X | X | X |
| Prototypes Bundle [38] | Constructionism<br>Intrinsic motivation | P | | | X | | | |
| DSLEP Bundle [9] | Gamification<br>Pink's motivation theory<br>The Flow | F/P | X | | X | | | |

NI means "not included".
[a]The types of knowledge are Factual (F), Conceptual (C), and Procedural (P).

## 3.3 Evaluation Aspects

Twelve of the seventeen articles reviewed included a game evaluation. All evaluations involved users and intended to measure users' abilities or opinions about the game.

Concerning the evaluated factors (RQ5), we identified fifteen factors which are listed in the second column of Table 4. It was found that most studies (eleven of thirteen) evaluated more than one factor. The factor classification framework suggested by [33] was used to classify the factors into seven categories. The factors identified most commonly fell under the learning, UX, and usefulness categories. Studies that evaluated perceived learning were classified under the usability category. Figure 1 shows the number of studies which were found to evaluate factors for each category.

Regarding the research design (RQ6), seven studies were classified as quasi-experiments, three studies as ad-hoc, three as non-experimental, and only one as experimental. The third column of Table 4 lists the research design used by each game.

**Table 4.** Evaluation aspects: Evaluated element, evaluation design, number of participants, instrument, and analysis methods.

| Game | Evaluated elements | Evaluation Design (N° participants) | Instruments | Analysis methods |
|---|---|---|---|---|
| Wu's Castle [16, 17] | Learning, enjoyability, preference, perceived learning, motivation, usability. | Quasi-experiment (27) Experiment (55) | Test Qualitative survey | DS: percentages, averages. IS: t-test |
| Star Chef [30] | Technology acceptance (usefulness, easiness, and attitude towards the tool) | Quasi-experiment (110) | Qualitative survey Interview Observation | DS: mean, standard deviation, and standard error IS: ANOVA Informal analysis |
| Stacks and Queues [32] | Usability, perceived learning, preference. | Non-experimental (32) | Qualitative survey | DS: histograms, percentages |
| Stack Em Up [22] | Suitability. | Non-experimental (15) | Qualitative survey | DS: histograms, percentages |
| Stack Game [13, 14] | Learning, motivation, usefulness, perceived learning, preference, clarity, provided support, enjoyability. | Quasi-experiment (29) | Test Qualitative survey | DS: mean, standard deviation, and percentages IS: t-test, Cohen's d |
| Ramle's Stack Game [36] | Learning, usability, user interface, interactivity. | Quasi-experiment (29) | Test Qualitative survey | DS: percentages. |

(*continued*)

**Table 4.** (*continued*)

| Game | Evaluated elements | Evaluation Design (N° participants) | Instruments | Analysis methods |
|---|---|---|---|---|
| Space Traveler [47] | Learning, motivation, perceived learning, enjoyability, and usefulness. | Quasi-experiment (13) | Test Qualitative survey | DS: mean, median, standard deviation, variance, histograms, percentages. |
| AVL Tree Game [40] | Enjoyability and engagement | Ad-hoc (5) | Observation Qualitative survey | Informal analysis |
| Elemental [7] | Learning, enjoyability, perceived learning, and preference. | Quasi-experiment (42) | Test Qualitative survey | DS: percentages, means, standard deviation, histograms. IS: t-test, Cohen's d |
| HTML5 Hanoi Tower [42] | Learning | Non-experimental (17) | Test Qualitative survey | DS: mean, standard deviation, and histograms |
| Recursive Runner [48] | Leaning, enjoyability, perceived learning, motivation, preference. | Quasi-experiment (31) | Test Qualitative survey | DS: average, medians, standard deviation, histograms |
| Critical Mass [29] | Learning, Preference, and perceived learning | Ad-hoc (42) | Assignment Qualitative survey | DS: percentages |
| Resource Craft [23] | Learning and self-motivation | Ad-hoc (102) | Qualitative survey | DS: percentages |

**DS** means "descriptive statistics". **IS** means "inferential statistics".

Concerning data collection tools (RQ7), thirteen evaluations were found to use a qualitative survey, seven a test or questionnaire, two an observation method, one an assignment, and one an interview. It is important to note that with the exception of the evaluation of *Star Chef* (which used the TAM scale [12]), all studies analyzed utilized an informal instrument (an instrument that was not validated or calibrated) to evaluate game factors. The fourth column of Table 4 lists the instruments used by each game.

In terms of data analysis methods (RQ8), twelve evaluations were found to use descriptive statistics (means, variance, standard deviations, histograms, and percentages), while only four were found to use inferential statistics (t-test and ANOVA). Finally, two studies were found to employ informal methods to analyze the qualitative

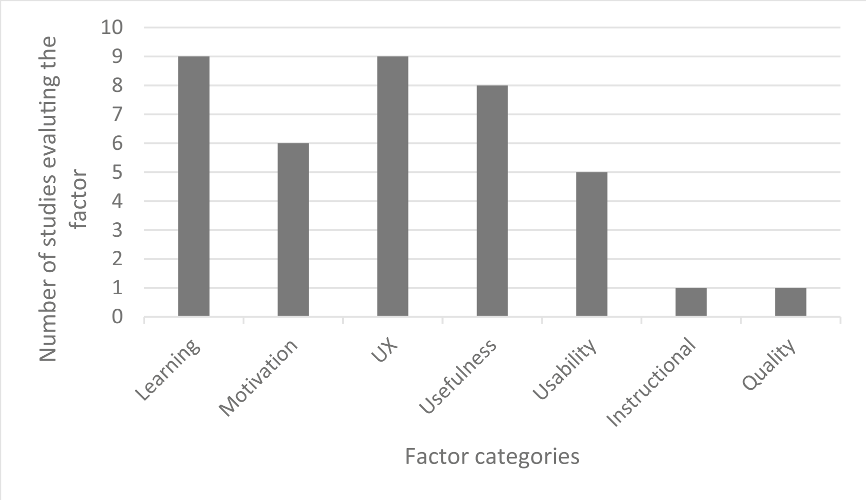


**Fig. 1.** Frequencies of the evaluated factors.

data collected from interviews and observations. The fifth column of Table 4 presents the methods used in each evaluation.

## 4 Discussion

Our results show that the most common data structure covered in the serious games reviewed was the stack; the stack appeared in seven of seventeen games reviewed. A reason for this finding may be that the stack is a simple but fundamental data structure, which makes it ideal for fast prototyping and testing of potential uses of learning games in the field. Additionally, stacks may appear more due to the fact that the Association for Computing Machinery (ACM) recommends that the stack be included as an essential topic in undergraduate programs [2]. However, we noticed that apart from the *Stack Game*, all the digital serious games that focus on stacks are trivial. For instance, three games used the Hanoi Tower puzzle as the main game challenge, while in the other three games, the only game mechanics available were the queue and dequeue operations. As a result, these games may fail to engage the player due to their lack of sophistication. In contrast, *Stack Game* uses the Hanoi Tower puzzle in a clever way. In this game, the player must arrange blocks of different colors in a certain order following the last-in-first-out principle to unlock doors. Additionally, *Stack Game* offers different challenges, such as puzzles, which require that players evaluate arithmetic infix and postfix expressions as well as execute coding puzzles. We suggest that following *Stack Game*'s example, serious games that teach data structures employ data structure properties in a clever and creative way to create more engaging game challenges and game mechanics. The more engaged a player is, the more motivated he or she will be, which helps to facilitate the learning process.

Furthermore, we noticed that most of the reviewed games focus on teaching simple data structures (e.g., array, 2D array, stack, queue, linked list, and dictionary) and recursive algorithms (e.g., Hanoi Tower algorithm, Fibonacci, Factorial, and Binary Search). Only a few games were found to focus on teaching medium-complexity data structures (e.g., binary trees and AVL trees) and algorithms (e.g., tree traversal and depth-first search). This finding suggests that more research on digital serious games that teach advanced data structures and recursive algorithms, such as complex trees (e.g., red-black trees or B-trees), graphs, and their associated algorithms is needed.

Concerning theoretical foundations, 65% (eleven of seventeen) of the studies reviewed reported a learning theory or principle. The most common theory observed was Constructionism (five of eleven) followed by scaffolding (four of eleven), a concept based on Vygotsky's Proximal Developmental Zone [35]. This finding is consistent with the results obtained in other literature reviews. For example, Wu et al. [46] performed a literature review of serious games for learning and likewise found that most of games reviewed reported a constructivist theory. In another literature review focusing on serious games for learning science, Cheng et al. [8] found that most of the reported learning theories were either constructivist or based on Vygotsky's theories. Similarly, our findings suggest that most of the reviewed works (eight of eleven) explain learning through games as an active process that requires the construction and socialization of knowledge (Vygotsky's theories).

In our review, only one study was found to explicitly report learning objectives. In general, learning objectives facilitate the extraction of cognitive processes and the type of knowledge delivered by a game. Consequently, it was necessary to deduce these aspects from the game description of the rest of the games.

We found that in almost all games reviewed (fifteen of seventeen), it was necessary for the learner to employ the *apply* cognitive process to achieve the learning activities. Additionally, the most common type of knowledge delivered by the games reviewed was found to be *procedural* (fourteen of seventeen). This finding was not surprising due to the interactive nature of video games. However, games with complex tasks that required higher cognitive processes were identified. For example, in order to succeed in the coding games reviewed, *Critical Mass* and *Resource Craft*, players had to employ the *create* and *evaluate* cognitive processes, the highest cognitive processes of Bloom's taxonomy. This finding confirms previous observations made by game scholars (e.g., [19, 39]) who suggest that video games support the acquisition of skills and knowledge that require higher cognitive states. Finally, concerning type of knowledge, it was found that some games used narrative elements to deliver factual and conceptual knowledge (e.g., *Elemental* and *Stack Game*). This indicates that game elements can be used to deliver different types of knowledge.

It is a concern that sixteen of seventeen games reviewed did not explicitly report the learning objectives of the games. Learning objectives are important because they define the level of mastery of a topic that a learner should have at the end of a learning experience [4]. Furthermore, learning objectives specify the scope of the learning material, tool, or program. It is desirable to define learning objectives using frameworks that systematically describe the complexity of tasks that learners are expected to master [4]. Normally, these frameworks are hierarchical, with their classification categories possessing an ordinal nature (e.g., SOLO taxonomy [4], Bloom's taxonomy [1], etc.). It is also desirable that learning tools, such as serious games for learning, state their learning objectives [31] during their design stage. By doing this, the designer is able to align the learning activities to fulfil the objectives and develop accurate assessment tools of the learner and the game itself. The latter aspect is quite important in terms of research which require proper assessment tools; without a proper assessment, it is not possible to develop good theory about serious games.

Concerning evaluation aspects, we found that in general, researchers were interested in evaluating games' (1) efficacy to teach data structures and recursion; and (2) affective outcomes. Most of the evaluations conducted were quasi-experiments; in total, thirteen games were evaluated using a quasi-experimental design. In contrast, only one study was evaluated using a full experiment. A reason for this finding may be that quasi-experiments are easier to carry out; researchers may not need to divide the sample into random groups, and they may not need a control activity. Therefore, this type of experiment is easier to design, execute and analyze than a full experiment. However, such results are not as conclusive as those obtained through a full experiment [26].

In terms of data collection tools, we found that with the exception of one instrument, all tools were informal. By informal, we mean instruments that were not validated nor calibrated to behave as a scale. Consequently, data collected using such instruments cannot be evaluated using parametric statistical methods such as t-tests or ANOVA. Excluding one evaluation, all collected data was analyzed using descriptive statistics. Of these, three studies employed parametric methods to analyze ordinal data (scores of tests) which is unfortunate as doing so departs from best practice [18]. Additionally, studies that used qualitative instruments (three of thirteen; e.g., interviews and observations) did not report any protocol describing how the data was collected and analyzed. Consequently, results obtained by these methods are not conclusive. Therefore, like other scholars (e.g., [44]), we suggest that more qualitative or mixed experiments be carried out to properly analyze the nature of learning through digital serious games.

## 5 Conclusion

This article has reviewed the state of the art of serious games that teach data structures and recursive algorithms reported between 1999 and 2019. In total, seventeen digital serious games were identified which together covered a total of nine data structures and six recursive algorithms with the stack appearing the most frequently. None of the data structures or algorithms covered were found to be advanced. Consequently, there is great potential for further research involving serious games that teach advance data structures. Additionally, our results showed that several serious games were able to provide players with tasks that required them to use the highest cognitive processes of Bloom's taxonomy. This finding suggests that serious games have the potential to provide users with learning activities that facilitate the acquisition of complex learning objectives. However, our results showed that improvements in the methodology used to evaluate serious games for learning in this field are sorely needed. For example, most games reviewed did not report the learning objectives necessary for posterior evaluation. Likewise, it was found that improvements in the selection or development of data collection instruments as well as the selection of analysis methods appropriated for collected data are needed. Finally, we noticed a lack of evaluations of games following experimental designs or qualitative methodologies. Improving evaluation methods will allow researchers to develop accurate theories regarding serious games and learning.

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