# Extracting Learning Analytics from Lightbot Gameplay Sessions

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***Abstract.*** *This paper presents a method for extracting and visualizing learning analytics from Lightbot using computer vision. Lightbot is a serious educational game that foments computational thinking and teaches introductory programming concepts. We collect information from recorded game sessions, such as the number of commands used, the effectiveness of the player's solution, and the number of times the player submitted their solution for assessment. We then use this data to create graphs that help education professionals understand the challenges and successes students find when using Lightbot as a teaching tool.*

**Keywords:** Learning Analytics, Computational Thinking, Computer Vision, Lightbot

## 1. Introduction

Game-based learning (GBL) is a pedagogical approach that promotes active learning by harnessing the power of games or its elements to involve and stimulate students through narratives and challenges [de Carvalho and Coelho 2022] [Xu et al. 2023]. One of the primary GBL strategies includes serious games. A serious educational game (SEG) is a specific type of game designed with the dual purpose of educating the player on a particular subject and providing an immersive, enjoyable experience [Laamarti et al. 2014]. They play an important role across many fields, including engineering [Matos and Sarinho 2023], mathematics [Ortolan and Modesto 2023] [Santos et al. 2023], and health education [Silva and Guerra 2023] [Gonçalves et al. 2023], to mention a few. Among the benefits are the active experimentation through simulations, improved content retention and increased student engagement; these factors boost overall student performance when compared to traditional methods [Kara 2021] [Arif et al. 2024].

In addition to these benefits, GBL strategies can significantly enhance computational skills, which have become integral to our digital society. Seymour Papert first mentioned "algorithmic thinking" in 1980 [Papert 1980] and Jeanette Wing brought renewed attention to computational thinking (CT) in 2006 [Wing 2006], defining it as "an approach to solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science". This area refers to the development of problem-solving and critical thinking skills [Troiano et al. 2019] [Akkaya and Akpinar 2022] [Nipo et al. 2023], which are essential to tackle computer programming activities. It was recently included in the Brazilian National Policy for Digital Education (NPDE) [Brasil 2023] as a core mechanism to foment digital literacy and development.

CT programming tools include text-based, visual block-based, and alternative visual programming tools [Manske et al. 2019]. Lightbot is among these tools; it is a serious game under the alternative visual programming tool [Gouws et al. 2013] category. Lightbot offers students an engaging way to learn about abstraction, recursion, and strategies for evaluating and enhancing existing solutions. In Lightbot, the player guides a robot from one starting point to a destination using a finite number of commands and functions. Each level becomes increasingly challenging as the player progresses, requiring more refined solutions. However, the game does not provide any feedback or insights that might guide player performance other than the number of movements made.

The data collected from the game sessions is also a source for Learning Analytics (LA), a field that focuses on using analysis models to understand and advise on learning [Minović and Milovanović 2013] by “appropriately visualizing these mechanisms for the user (instructor, instructional designer, institution, parent and/or learner) and empowering him/her to interpret and intervene in the process” [Shoukry et al. 2014]. Learning analytics is concerned with delivering actionable insights through visual reports to help instructors and learners optimize teaching and learning practices [Viberg et al. 2018].

The insights derived from an LA process can be used to created adaptive serious games that enhance engagement and challenge players with problems that align with their current abilities [Hooshyar et al. 2017] [Hare and Tang 2023]. Therefore, this paper contributes to the literature with a learning analytics method to analyze and extract learning data from recorded Lightbot gameplay sessions using classic computer vision methods. We collect metrics, such as the time taken to complete a level, the number of commands used, the effectiveness of the player’s solution, the number of times the player submitted his solution for assessment, and the number of mistakes per command block. These metrics are presented to educators through visual graphs, enabling them to provide personalized feedback to students and to decide where to focus their efforts in fomenting computational thinking and teaching programming concepts while using the Lightbot game as a tool.

## 2. Theoretical Foundations and Related Works

Research in Serious Educational Games (SEG) and Computational Thinking (CT) has extensively explored how to foster the development of critical thinking and problem-solving skills via interactive gaming platforms [Jeon and Song 2019]. Analyzing player behavior in SEGs is also essential for understanding how players interact with the game and how they develop solutions to in-game challenges. Player Modeling and Game Learning Analytics are fields that focus on collecting game data, understanding player behavior, and providing insights to improve the user experience.

Game Learning Analytics (GLA) is an emerging discipline that combines concepts from learning analytics and game analytics to systematically collect and analyze data on player interactions within educational games [Freire et al. 2016]. This method offers valuable insights into student engagement with educational content, enabling real-time adaptation and personalized learning experiences. Additionally, [Massa and Kühn 2018] surveyed various application of GLA , highlighting that SEGs designers should monitor and evaluate player performance and learning outcomes using traces, such as key actions like key presses, mouse clicks, and in-game decisions.

Research, such as the work of [Minović and Milovanović 2013], has demonstrated the effectiveness of real-time LA in adjusting learning experiences based on the learner's progress and challenges. This adaptive approach not only maintains an appropriate level of difficulty but also provides data-driven insights, enabling educators to better assess student learning performance and the effectiveness of game-based learning [Shoukry et al. 2014].

Research by [Jeon and Song 2019] on CT games has proposed models that use learner data to customize challenges and feedback, supporting personalized educational journeys. CT games can be found on multiple platforms, such as virtual reality (VR) [Nipo et al. 2023] and mobile devices [Gouws et al. 2013]. [Nipo et al. 2023] presents the ”Robo-Think” project, a VR SEG aimed at developing CT skills through the simulation of real-world programming challenges in a virtual space.

Lightbot serves as an example of how SEGs can be strategically employed to develop critical thinking and problem-solving skills foundational to CT [Aedo Lopez et al. 2016]. Studies such as [Gouws et al. 2013] underscore the potential of SEGs to serve as powerful pedagogical tools in educational settings, particularly in CT.

Several works have shown successful applications of Lightbot or its variations. [Souza et al. 2018] crafted a board game inspired by the Lightbot mechanics to teach mathematics and computational thinking. In this game, the “light” command became a challenging mathematics puzzle. Students reported a positive and enriching experience with the game, enhanced by its collaborative aspect. [Urquizo et al. 2021] found statistical evidence that an experimental group performed better in exams after playing the game compared to a control group. [Freitas and Morais 2019] and [Bonfim et al. 2023] evaluated the game as an effective tool for introducing programming and logic concepts to new learners.

In the context of GLA metrics within CT games, [Varghese and Renumol 2023] review various techniques from literature, such as data mining and clustering, which are utilized to analyze game logs and predict the development of students' CT skills. [Israel-Fishelson and Hershkovitz 2021] examined task difficulty through metrics like the number of attempts to achieve a solution and the scores obtained.

Furthermore, the application of LA in SEGs such as Lightbot highlights the pivotal role of real-time data collection and analysis in enhancing educational methodologies. Through comprehensive monitoring and assessment of player interactions within the game, educators can deploy tailored instructional strategies and provide personalized feedback that aligns with individual learning paths [Fernandez et al. 2022].

This research paper proposes GLA metrics for analyzing and extracting game data from recorded Lightbot gameplay sessions. Our contribution consists of applying computer vision techniques to extract and analyze player behavior in Lightbot. In the Results section, we detail how these metrics correlate with the player's performance in learning CT skills.

## 3. Lightbot

Lightbot is a single-player serious game available on web and mobile platforms. Both versions share the same game mechanics but differ in the user experience and interface. This work used the mobile version. The game objective is to guide the main character, a robot, from a starting point to a destination. Players have a finite set of predefined commands to solve each level, which gradually increases in difficulty. The game takes place on a grid of tiles, with blue tiles that need to be activated using the appropriate command. Players advance to the next level once all the correct tiles are active. The initial levels (1-4) serve as an introduction, teaching players the game mechanics; further levels introduce additional challenges, such as the need to repeat behaviors and explore the game map vertically, as seen in figure 1.

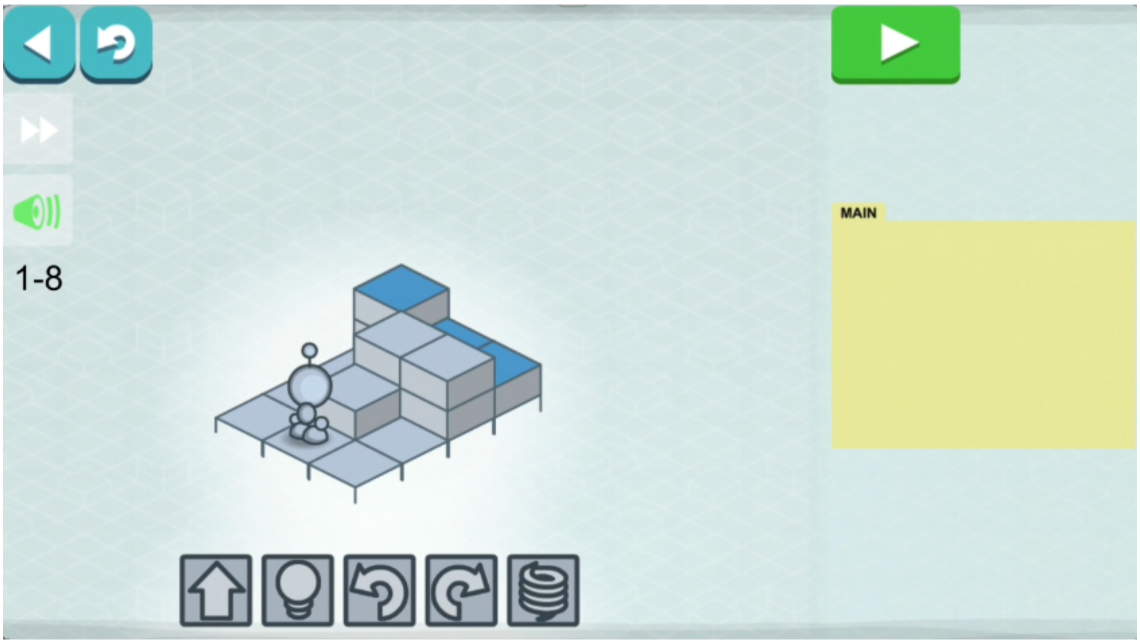


**Figure 1. Lightbot mobile - level 8**

The overall goal is to foment computational thinking and teach introductory programming concepts, such as the sequential control flow (the execution of commands in their order of creation), procedures (groups of commands that explore a pattern by executing the same actions), loops (group of code commands that repeat), and debugging (running and re-running a program to assess the quality of solutions and fix mistakes). However, the game fails to provide feedback or insights that could guide players to perform better other than the total number of movements a player makes.

**Figure 2. Lightbot commands**


**Figure 3. Lightbot functions**

Figure 1 presents the 8th game level. The "main method" represents its counterpart in programming languages and is executed when the player presses the "Play" button.

The game gives the player a set of commands, as seen in figure 2. The solution emerges from the combination of these blocks of “code”. The first button, starting from the left, represents the “move forward” function; then we see the the “light” command, responsible for changing the color of the tiles; the following two buttons represent “turn left” and “turn right”, respectively; the last button represents the “jump” method, which allows the robot to visit upper tiles; The player can also use functions through the commands “P1” and “P2”, as seen in figure 3. It is possible to create repeatable behaviors inside these methods.

## 4. Methodology

This research employs a structured methodology to extract and analyze learning analytics from gameplay sessions in Lightbot, a popular educational game designed to teach programming concepts.

### 4.1. Experimental Design

The experimental design is divided into four main steps, as described below:

1. **Data Collection:**
    - *Candidate Selection:* We selected two children (aged 7-12) to play Lightbot for the first eight levels. This selection was based on the assumption that children are the primary target audience for the game, and their gameplay sessions would provide valuable insights into the effectiveness of the proposed learning analytics.
    - *Gameplay Recording:* Sessions were recorded using scrcpy [Vimont and Contributors 2023], which mirrors the screen of Android devices to a computer, allowing high-quality video capture. In every session, we were interested in the player-issued commands and the game’s responses on each level.
    - *Metadata Definition:* Each recorded session is accompanied by metadata, such as the player’s name, the date and time of the session, and the current level.
2. **Data Processing:**
    - *Frame Extraction:* Game sessions are broken down into individual frames to isolate specific player actions and game state changes.
    - *Game Elements Extraction:* Key game elements, such as block commands and the play button are detected in which frame using a template matching algorithm.
    - *Command history:* The sequence of commands issued by the player is reconstructed from the detected game elements and saved in JSON format.
3. **Implementation of Learning Analytics:**
    - *Metric Development:* We developed the learning analytics metrics proposed in section 4.2 to assess the learning performance of selected candidates. We consider the number of run attempts, mistakes by level, time to complete a level, total number of errors per level, number of block modifications per level, and overall solution efficiency.
4. **Evaluation of Results:**

- *Extraction of LA metrics:* From the sequence of commands issued by the player, we extract the metrics defined in section 4.2.
- *Analysis of LA metrics:* A manual analysis is made from the extracted metrics to identify patterns and trends in player performance.
- *Results plotting:* We plotted graphs that allow an education professional to visualize the progress of the player across several game levels.

By the end of this process, the extracted learning analytics can help education professionals offer personalized feedback to students and develop teaching strategies that address the specific challenges faced by individual students or classrooms. In this manner, the LA provided by this method for Lightbot will enhance the overall teaching and learning experience.

### 4.2. Learning Analytics metrics

This section outlines the extracted metrics from Lightbot gameplay sessions. These metrics are specifically chosen to gauge various aspects of learning and engagement effectively:

| Metric | Description |
|---|---|
| Time Spent in a Level | Measures the time a player spends on each level in seconds, providing insights into the level's difficulty and the player's engagement. |
| Total Number of Mistakes | Counts all errors made by the player, indicating areas where players commonly struggle. |
| Number of Mistakes by Block Type | Categorizes mistakes by command block, helping pinpoint specific conceptual misunderstandings or difficulties with certain programming constructs. |
| Number of Run Attempts | Tracks how many times the player submitted his solution for assessment before succeeding, reflecting their persistence and trial-and-error learning process. |
| Number of Block Modifications | Tracks how many times a player changes the block configurations before submitting the solution for verification. |
| Solution Efficiency | A metric that assesses the efficiency of the player's solution compared to the optimal solution. |

**Table 1. Metrics for Assessing Player Performance**

The solution efficiency is given by the equation below.

$$E = (1 - \frac{U - O}{O}) * 100 \quad (1)$$

In equation 1, E represents the efficiency score, U represents the length of the user's solution, and O represents the length of the optimal solution. The length refers to the number of commands used. This score shows how succinctly a player can complete the objectives by providing a concise and effective problem-solving strategy.

These metrics not only provide a quantitative assessment of player performance but also offer valuable insights that can be used to tailor educational content and difficulty settings in real-time, thereby enhancing the educational impact of the game. By analyzing these metrics, educators and developers can identify key learning hurdles and optimize the game to better serve educational goals.

### 4.3. Frames extraction and processing

In our analysis, the first step is to capture continuous gameplay footage through video recordings. We used the `scrcpy` tool to mirror gameplay from Android devices to a PC, ensuring high-resolution captures. We collected 16 gameplay sessions where two children (aged 7-12) played the game for the first eight levels. These videos were sufficient for assessing the proposed data extraction and subsequent metric calculation techniques. From every video, we extract frames at regular intervals to analyze the sequence of player actions and game responses.

We use OpenCV in Python to analyze the extracted frame and understand the player's interaction with the game at a given moment. Our focus is to identify the list of game commands issued by the player, which are visible as icons on the game's interface. Each command icon, such as "move forward" or "turn left," was manually cropped from a screenshot of the game and then stored as a template image. These templates help the system recognize command icons in each game frame using the computer vision template matching technique provided by OpenCV's `matchTemplate` function. Here is a rundown of the first stage to get the position of each command icon in the game frame:

- **Template Matching:** In each frame, the region of interest (ROI) is the area where command icons are displayed. This ROI is converted to grayscale to simplify the analysis. We apply the template matching technique to find occurrences of each command icon within the ROI. To count how many times the player runs the game, we also define a ROI in the region where the play button is located.
- **Thresholding and Non-Maximum Suppression:** We use a correlation coefficient threshold to identify matches. To refine these matches and reduce redundancy, non-maximum suppression is applied to the bounding boxes of the detected icons.

In the post-processing step, we use the positions of the identified command icons to reconstruct the sequence of commands issued by the player and perform the following operations:

- **Spatial Sorting:** Detected icons are sorted spatially from bottom to top and left to right to logically reflect the command execution order. From the sorted list, we reconstruct the sequence of commands issued in the frame
- **Metadata Annotation:** Each frame is annotated with metadata that includes the frame number, detected commands, and their sequence. This metadata is crucial for aligning game events with player actions.

The combination of frame extraction and detailed image analysis allows us to obtain the list of commands issued by the player and then calculate all the metrics defined in section 4.2.

## 5. Results

Following the methodology described in section 4, we installed the Android version of Lightbot v1.1.6 in a Samsung S10e device running Android 12. From the collected gameplay recordings, our method generates graphs based on the defined metrics. Figure 4 shows how many times a player submitted his solution for assessment (metric 4) and the number of block modifications (metric 5) in each level.

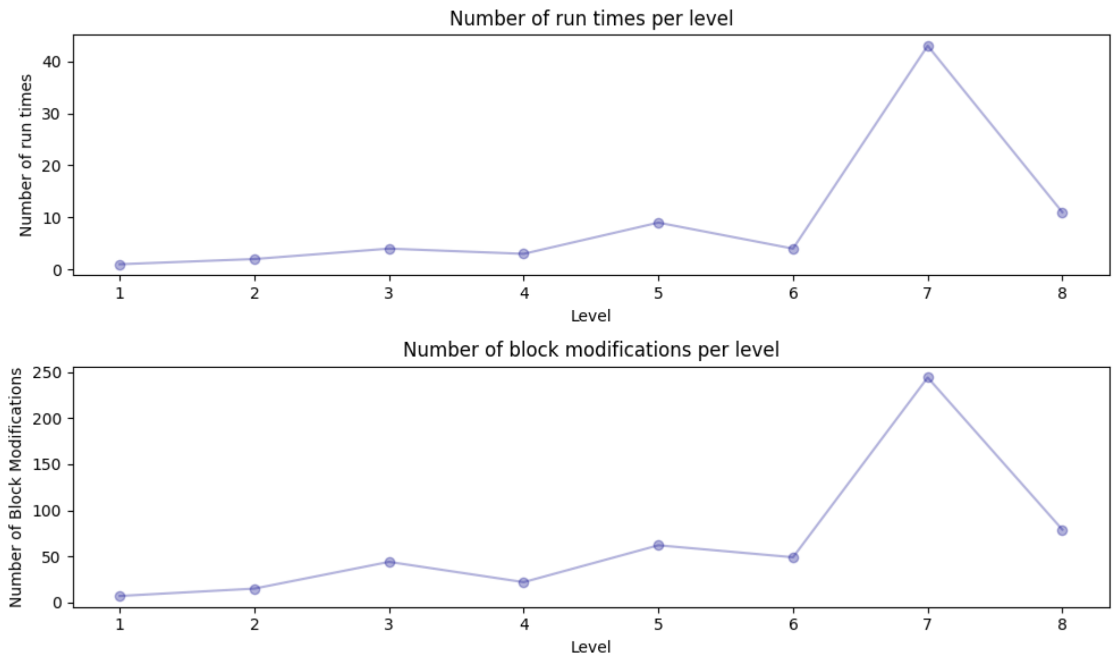


**Figure 4. Number of run attempts and block modifications per level**

We want to emphasize that at levels 3 and 6, the participants produced more block changes than run attempts. It could suggest that individuals are attempting to visualize and discover a solution before submitting it rather than relying on a blind trial-and-error approach.

The first levels (1-4) introduce the game and teach game mechanics; therefore, figure 5 illustrates that the player spent less time in these levels. We also noticed that level 7 was the most difficult, which may indicate that the player found one or more concepts challenging to grasp. The graphs in figure 5 corroborate with this finding by showing that the player spent a significant amount of time in level 7 compared to other levels while making more mistakes to find the solution.

Figure 6 shows the efficiency metric for each level. The metric becomes particularly interesting when a level offers multiple potential solutions with varying lengths (measured by the number of commands issued) in contrast to the solution length proposed by the player.

Figure 6 illustrates the frequency with which the player misplaced commands while crafting the solution for level 7. The data suggest that the "forward" command is relatively easy to conceptualize, whereas commands like "right" and "left" are more challenging. This difficulty is likely due to the isometric game camera, which simulates

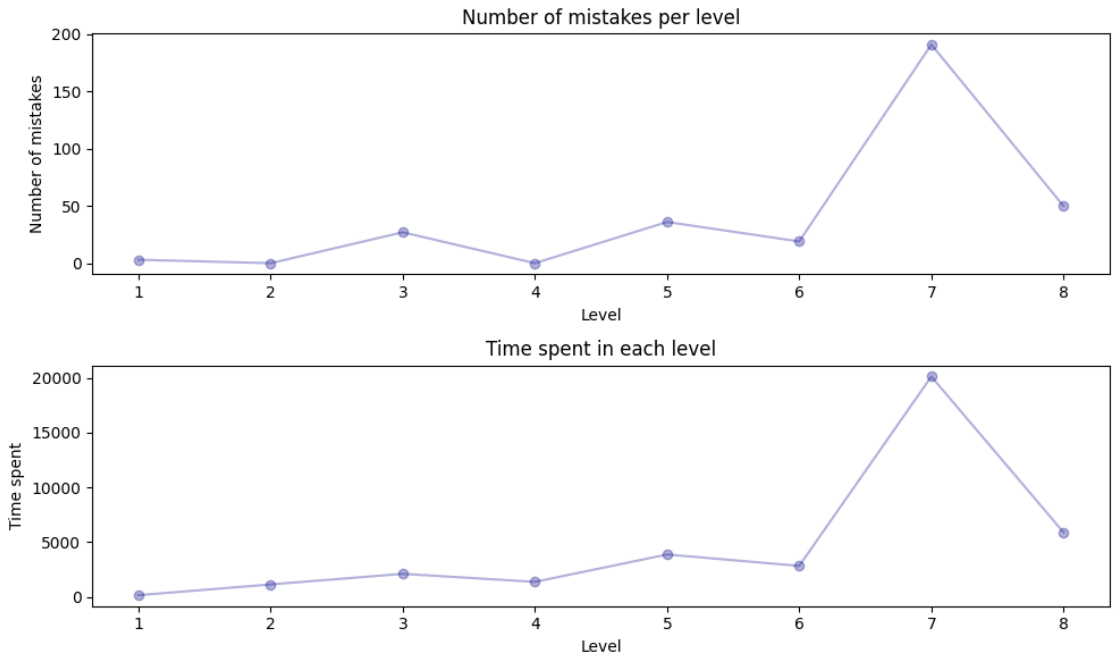


**Figure 5. Total mistakes and time spent per level**

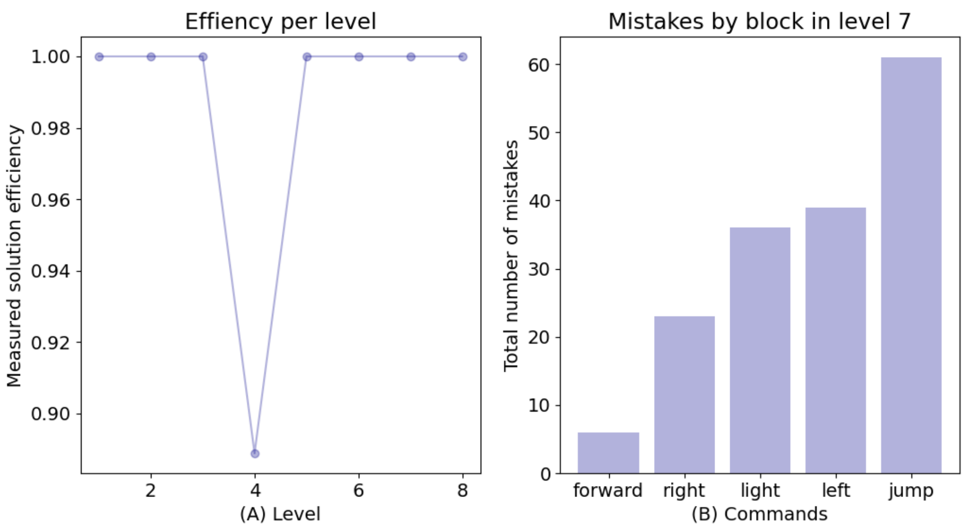


**Figure 6. Solution efficiency and command mistakes per level**

a 3-dimensional environment in a 2-dimensional game. The static nature of this camera angle makes it harder for players to correctly visualize directions such as right or left.

Our findings align with previous studies on educational games and computational thinking. For instance, Gouws et al. [Gouws et al. 2013] highlighted the potential of exploring iterative problem-solving when playing Lightbot, which corroborates our observations in levels 3 and 6. Educators can leverage this information by encouraging similar practices in classroom activities, promoting a culture of experimentation and iterative improvement.

Furthermore, our results regarding the difficulty of level 7 are consistent with findings by Urquizo et al. [Urquizo et al. 2021], who reported that more advanced levels in Lightbot challenge students' understanding of complex programming concepts. These similarities reinforce the validity of our metrics and analysis methods. Educators might consider incorporating more detailed explanations, hands-on activities, and peer collaboration opportunities to help students grasp these difficult topics.

The visual analysis of student progress while playing Lightbot provides instructors with valuable information. While students can also gain insights into their own performances, the primary audience for this analysis is instructors. They can use this information to make pedagogical decisions, such as addressing specific topics in classroom discussions or emphasizing certain concepts, like decision structures, to guide students in their learning journey.

## 6. Conclusion

This paper presented an application of learning analytics (LA) through a method for extracting, evaluating, and visualizing player performance while playing Lightbot, a serious game that teaches computational thinking and introductory programming concepts. The main steps consisted of recording gameplay sessions, extracting key game elements in each video frame, calculating desired metrics (run attempts, mistakes by level, time to complete a level, total number of errors per level, number of block modifications per level, and overall solution efficiency) and generating a final report for each metric by player to allow professors to make informed decisions about learning progress and directions. Besides, the method lets us understand the effectiveness and appeal of game design elements by providing insights into how players perceive the usage of game commands. In Lightbot, we notice confusion between the "left" and "right" directives due to the isometric game camera. Game developers could use these metrics to guide the solution to these pitfalls while implementing Lightbot-like games.

The proposed method achieved the established goals of providing insights and information about player progress and performance across levels during the game sessions. Future works might include the creation of a dashboard where teachers will find usage metrics for all students engaged with the game. Another possibility is the automation of game-level solutions using computer vision to find the best one given a level's image. We also see log collection and mining as a viable alternative to collecting student engagement and performance data in such games.

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