Data science meets standardized game learning analytics

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***Abstract*—Data science applications in education are quickly proliferating, partially due to the use of LMSs and MOOCs. However, the application of data science techniques in the validation and deployment of serious games is still scarce. Among other reasons, obtaining and communicating useful information from the varied interaction data captured from serious games requires specific data analysis and visualization techniques that are out of reach of most non-experts. To mitigate this lack of application of data science techniques in the field of serious games, we present T-Mon, a monitor of traces for the xAPI-SG standard. T-Mon offers a default set of analysis and visualizations for serious game interaction data that follows this standard, with no other configuration required. The information reported by T-Mon provides an overview of the game interaction data collected, bringing analysis and visualizations closer to non-experts and simplifying the application of serious games.**

Keywords—serious games, learning analytics, xAPI, dashboards, data science, visual analytics

I. INTRODUCTION

Serious Games (SGs) is a broad term that encompasses any game with a main purpose beyond entertainment [1]. Typical purposes include teaching knowledge, raising awareness about issues, or changing the attitudes or behaviors of its players. SGs have been applied in a wide range of fields, including education, healthcare, communication, or politics [2]. In the educational field, COTS (Commercial Off-the-Shelf Games) videogames can also be used for educational purposes [3], although there may be more barriers to adopt them in the classroom compared to serious games.

The application of games in educational scenarios presents multiple benefits: games provide an immersive learning environment, where risky or complex scenarios can be tested in safety while providing immediate feedback to players about their actions, and breaking the common 10-minute barrier of attention [4]. In this way, videogames allow the player to play an active role in their learning process.

Despite these benefits, the application of serious games is still limited. Among the barriers that exist when applying the videogame in the classroom are: the limited duration of typical class periods vs. that of games, the lack of definition of the role of teachers during game sessions, together with their low familiarity with serious games; the hardware infrastructure of schools; and the lack of resources to evaluate and track student progress [5]. Among these limitations, we highlight the fact that educators do not have information about what is happening in the game; instead, games act as a black box, and teachers have no control or insight into what is happening while students play. Therefore, it becomes very difficult to use this type of learning tool to effectively assess players.

A commonly used technique evaluate players is to make them fill out a questionnaire before playing the game, and a subsequent questionnaire after playing the game, and then compare both responses to measure the effect of the game on its players [6]. This methodology, however, also has drawbacks, as the measurement of learning is carried out externally, outside the learning environment, and taking a questionnaire could have additionally negative effects on players' performance [7]. Moreover, when only applying questionnaires, educators do not receive any information about the behavior and choices/answers made by the players, neither during nor after the game.

The problem of user tracking and evaluation is an inherent limitation to the use of new technologies in the classroom. However, it is possible to apply Learning Analytics techniques to address it. Learning Analytics (LA) are defined as: the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [8]. The educational contexts in which learning analytics are most popular are learning management systems (LMSs) such as Moodle, and in massive open online courses (MOOCs). These massive courses have been the biggest driver of analytics due to the large number of students involved, making it infeasible to track each student individually using traditional methods. This data-based approach also aligns with the current trend in many other fields where data science applications are growing dramatically, and in particular in education, where data-based approaches have been identified as one of the biggest challenges, through the fields of Educational Data Mining and Learning Analytics [9].

In the context of serious games, the application of this technique is called Game Learning Analytics (GLA) [10], and helps to relate gameplay with learning, providing a more evidence-based measure of players' performance. The information gathered from players' interactions can help, first, to validate the game and its design [11], and also to assess players, as defined in the field of *stealth assessment* [12]. However, the use of these techniques and data science associated with games is very limited due to infrastructure problems in the school, their complexity for educators, and the cost personalizing analyses to each specific serious game.

In this paper, we present T-Mon, a platform to tackle some of the previously identified issues when analyzing interaction data from serious games, by providing a default set of visualizations for any serious game data collected using a standard and validated format. The rest of the paper is structured as follows: Section 2 presents some related work on Game Learning Analytics, and the standard data format used to collect data from serious games (xAPI-SG); Section 3 presents T-Mon, the platform created to simplify the analysis and visualization of data collected from serious games; finally, Section 4 discusses the platform and presents the conclusions of our work.

II. Related Work

Learning Analytics (LA) has the potential to provide precise and evidence-based information about the process and progress of learners in an educational environment. LA has been used for many purposes, such as: enhancing the learning experience, analyzing the impact of interactions between students in learning, supporting the evaluation of learning designs, predicting students at risk of failing, predicting dropout in MOOCs, making sense of multimodal data and, more broadly, modelling players and predicting their performance [13]. However, there are still many remaining challenges, including: compliance with privacy requirements, data heterogeneity and ownership, lack of technology frameworks, and the lack of generalization of applications and tools [14]. Authors have also pointed out the need for evidence of the long-term impact of LA practices on learning and teaching practice.

LA techniques can also be applied to serious games, where players/learners interact with the learning environment (in this case, the game) creating a rich interaction data that can be analyzed for multiple purposes. In particular, the application of LA in the context of serious games has had two main focuses: predicting players performance, and visualizing players results [15]. The large amount of LA data gathered from serious games can also be analyzed with more complex data science techniques to obtain deeper information. Research in this area has focused on predicting the effect of the game on players based on their interactions and creating different players profiles to analyze and understand their learning process in the game [16].

The analysis of interaction data from serious games can be performed both at near real-time (while students are playing) and/or after the gameplays have finished:

- In real-time, the data collected and analyzed can tackle the issue of teachers losing track of players during the application of games: while students play, teachers can receive information about students' actions and progress, gaining insights about their learning and intervening if necessary. These real-time metrics can also be used to evaluate players at real time, comparing results and choices/answers among different students.
- In batch (offline), once all students have finished, more complex analysis techniques on the aggregated data can provide further insights about the results. For instance, players could be clustered or classified, to provide information about the different players' profiles and their learning status and needs. The aggregated results could also be combined and compared with results from other activities, or even with other data sources.

While the use of LA techniques can be effective in many educational aspects related to serious games, its integration and application in real scenarios is complex, from the infrastructure and format of the data to the type of analysis and the goals to be addressed. Chatti et al. presents a model for the application of LA with four dimensions (Fig. 1): the "what" defines the data collected by the system, its management and context of use; the "why" defines the purposes of analyzing the data collected (including monitoring, intervention, or reflection); the "how" defines the method to apply in the analysis of such data; and finally, the "who", the stakeholders to whom the analysis is directed [17].

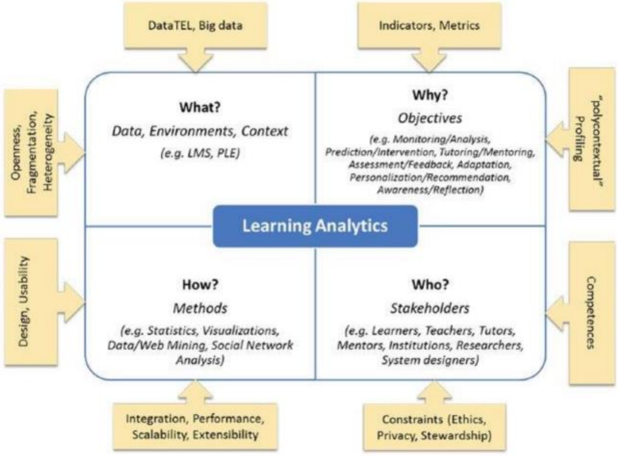

Fig. 1. Learning Analytics model dimensions [17].

Freire et al. [10] presented an abstract overview of a Game Learning Analytics (GLA) system, detailing all the steps of such architecture. Their described process starts when the game sends data to a collector. The data collected is aggregated to generate information to feed reports and visualizations (in real-time or offline) and assess students. The process ends in the adapter component, that provides feedback to adapt the game to players (Fig. 2).

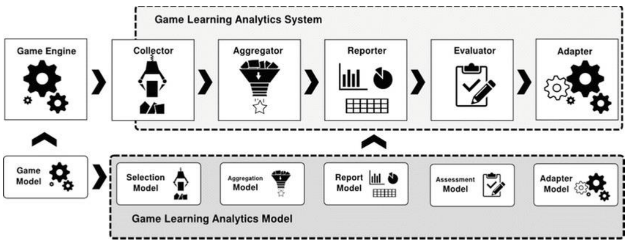

Fig. 2. Conceptual architecture of a Game Learning Analytics System, from [10].

The final step to turn the collected interaction data into usable and understandable information is to communicate it to the suitable stakeholders in a clear way. Visualizing the aggregated data, or the results of the performed analysis, in dashboards or visualizations could achieve this purpose. Lower-level analytics details can be hidden when required, providing an overview of the results simplified for the relevant stakeholders (students, teachers, researchers). Many exploratory studies have created their dashboards, but more research is needed to compare dashboards designs. Learning Analytics dashboards display learners' data to make informed decisions about the learning process [18]. Examples of Learning Analytics dashboards have been developed, for instance, to support communication between students and advisers, to visualize learners' actions and GLA information [19]. Although the main goal of LA dashboards is to make learners aware of their learning process, authors have pointed out that, beyond that awareness, dashboards should also have aim to improve competencies.

The information obtained analyzing the collected interaction data can be integrated into the different phases of the videogame lifecycle and targeted to different user profiles with different goals. During development, the integration of such analyses is used to validate the design and find possible software errors. When validating the game, analytics helps to study the game's effect on players, as well as their interactions with the game. Finally, during deployment and application in real scenarios, analyses help teachers to assess players and track their progress during their sessions. Throughout this lifecycle of serious games, the nature and content of collected data can vary; large volumes of data will require analytics systems ready to process them, and the time and cost to create, configure and use those systems can easily be out of reach for many potential users. But before requiring a full analytics platform as may be required for truly large-scale deployments, during the SG development phase, the design and development team can benefit from a more agile approach – which we could term a "minimum viable analytics" (MVA) solution.

Increasing use of analytics is not only a problem of having a platform that can display it. Serious games must be created with analytics in mind, and the games must have an in-built mechanism to send analytics data for analysis. To reduce some of the barriers that currently exist in GLA, some platforms to simplify the collection and application of user interactions data have been developed: the serious games authoring tool uAdventure [20] integrates default learning analytics in its created games to simplify the definition and collection of such interaction data, while the validation tool SIMVA [21] aims to simplify the performance of experiments where interaction data is collected from serious games, providing an easy-to-use interface to then gather all the collected data.

In order to simplify the integration of analytics and to generalize their use and compatibility with other data sources one of the first steps is to use standards in the interaction data collected during the game sessions. These data standards should provide a clearly defined format to collect the interaction data, helping other researchers and users to clearly understand the information collected and simplifying integration with other tools and ecosystems. Besides the use of a standardized data format, privacy and anonymity requirements should be met, to comply with all applicable regulations (e.g. GDPR). One of the most widely used information standards in the educational field is xAPI. This standard allows the creation of specific profiles to adapt to the needs of the different educational resources that exist, such as serious games.

A. *Experience API for Serious Games*

The Experience Application Programming Interface (xAPI, for short) is a data specification created by a community led by the Advanced Distributed Learning (ADL) initiative, a program under the Department of Defense of the United States of America [22]. xAPI is based on activity streams, a standard to represent activities, and aims to provide a standard to communicate information about learners' activities in learning systems. The main concepts of xAPI are verbs, activity types and extensions. Data traces in xAPI (called *statements*) are JSON-based and represent learning activities. Each statement contains three main fields: *actor*, *verb*, and *object*. The *actor* represents the one who carries out the action, the *verb* is the action itself, and the *object* is the item that receives the action. Extensions may be included in the statements to provide further information about the learning activity such as: context, results, timestamp, etc.

For situations that have specific requirements that go beyond the ones defined in Experience API, specific xAPI Profiles can be created to provide the means to comply with expertise in that topic area. An xAPI Profile is defined as "the human or machine-readable documentation of application-specific concepts, extensions, and statement templates used when implementing xAPI in a particular context". xAPI Profiles provide a specific set of verbs, activity types and extensions to meet the needs of a specific area. Students' results in xAPI format can be stored in Learning Record Stores (LRSs). The data representation format is used to store the data in LRSs and to help transfer and combine data from multiple LRSs.

The xAPI Profile for Serious Games (xAPI-SG) was created to identify and standardize the common interactions that can be tracked in a serious game. An interaction model for serious games was created and then validated and published with ADL to be the official xAPI Profile for Serious Games [23]. The Profile defines a set of verbs (*accessed*, *completed*, *initialized*, *interacted*, *pressed*, *progressed*, *released*, *selected*, *skipped*, *unlocked*, *used*) and activity types (*area*, *controller*, *cutscene*, *dialog-tree*, *enemy*, *item*, *keyboard*, *level*, *menu*, *mouse*, *non-player-character*, *quest*, *question*, *screen*, *serious-game*, *touchscreen*, *zone*) that can be used to define the data from players' interactions in the game. This set of verbs and activity types covers the most common interactions that occur in serious games, including information about *completables* (game parts that can be started, progressed in and completed), or *accessibles* (game areas that can be entered and skipped). For instance, Fig. 3 depicts an example


```
{
  "actor": {
    "name": "John Doe",
    "mbox": "mailto:johndoe@example.com"
  },
  "verb": {
    "id": "https://w3id.org/xapi/adb/verbs/selected",
    "display": { "en-US": "selected" }
  },
  "object": {
    "id": "http://rage.e-ucm.com/activities/Countrix/questions/Capital_of_Spain",
    "definition": {
      "type:" "http://adlnet.gov/expapi/activities/question"
    }
  },
  "result": {
    "response": "Lisbon",
    "success": false,
    "extensions": {
      "https://w3id.org/xapi/seriousgames/extensions/health": 0.34
    }
  }
}
```


Fig. 3. Sample xAPI-SG statement capturing that the actor (John Doe) has selected a false response (Lisbon) in a question (Capital_of_Spain), and his current health is 0.34.

xAPI-SG statement representing that a player (given in the *actor* field), has selected (*verb* field) an incorrect response (given in the *response* and *success* fields of the *result*) in a question (*object* field). Using the xAPI-SG standard, we have developed T-Mon, a platform to simplify the analysis and visualization of interaction data from serious games.

III. T-Mon: A Platform to Simplify and Automate the Data Analysis in Serious Games

T-Mon provides a default, game-independent set of analysis and visualizations to obtain information of serious games interaction data that follows the xAPI-SG standard. T-Mon contains a set of Jupyter Notebooks that process the xAPI-SG statements, analyzes them, and displays a default set of visualizations that provide a quick overview of its contents. All this process occurs automatically after the interaction data is loaded in T-Mon, providing an overview of the information collected in the data. The displayed information is useful to analyze the collected data and visualize the results of players' actions in the games.

The main Jupyter notebook in T-Mon expects a JSON file with the list of xAPI-SG traces to be processed. Certain xAPI traces, not specific to the xAPI-SG Profile, could also be processed by T-Mon; but the analysis mainly focuses on the specifics of the Serious Games Profile. The traces in the JSON file are then analyzed by T-Mon. The xAPI-SG traces are read in order and processed individually. For each player (given in the *actor* field of the traces), T-Mon stores a set of higher-level game learning analytics information, creating a set of variables that constitute the player profile. The information on each player profile is updated with each subsequent trace corresponding to the same player. The information for each player is stored in higher-level metrics that differentiate the information gathered for each type of verb included in the Profile: *initialized*, *completed*, *progressed*, *accessed*, *skipped*, *interacted* and *selected*.

The default set of visualizations is then filled with the information aggregated in each player profile. T-Mon's interface displays the results in visualizations grouped in 7 tabs containing information about: players' progress, use of videos, completables, alternatives, interactions with items, accessibles and menus (Fig. 4). We currently provide default game-independent visualizations with the following information:

- Start, completion and progress of players in the SG
- Final progress in completables, with evolution over time
- Final scores obtained in completables
- Maximum and minimum completion time in completables
- Correct and incorrect responses in alternatives per player, and per alternative
- Responses selected in questions (alternatives)
- Interactions and actions with items
- Videos (accessibles) seen and skipped
- Accessibles accessed
- Selections in menus

Fig. 5 and Fig. 6 display some of T-Mon's default visualizations, populated with sample xAPI-SG. The plot style

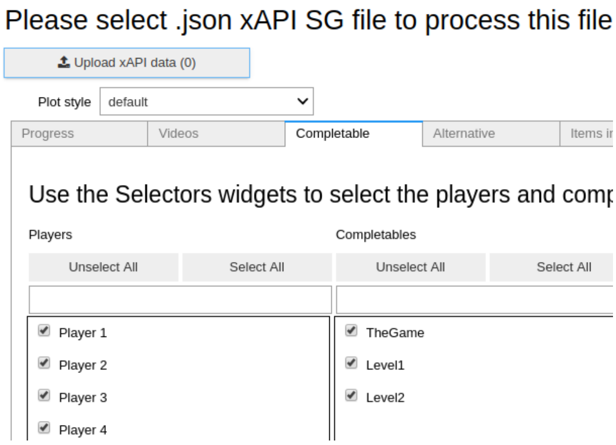

Fig. 4. T-Mon configuration options. From top to bottom: button to upload the xAPI-SG file, plot style dropdown, the seven visualization tabs, selection of players and other data (e.g. completables).

of the visualizations can be changed using a drop-down menu. The data displayed can be modified by selecting or removing specific player data from the visualizations, or specific items. For example, in the *completables* tab, specific completables can be selected, filtering the corresponding view so that data from non-selected completables is filtered out. These configuration options are displayed in Fig. 4. Visualizations can be further configured by: selecting whether data should be displayed in absolute values or as percentages, selecting the number of items to appear per visualization (if there is too much data, this can be divided into multiple visualizations), and ordering the data in the x axis (in alphabetical order, from higher to lower values or from lower to higher values). Visualizations with information per time can be configured to be displayed in absolute time or relative time (that is, relative to the first data point for each player, to compare between sessions carried out in different dates).

To expand the functionality of T-Mon, we have configured integration with SIMVA (which stands for Simple Validator), a tool to simplify experiments to validate and deploy serious games [21]. SIMVA manages the commonly used questionnaires, as well as the interaction data, storing all results, and linking all data from each player using anonymous identifiers. Integration between T-Mon and SIMVA allows interaction data collected from experiments with serious games in SIMVA to be accessed seamlessly from T-Mon. The default analysis and visualizations available are then applied to the data as provided by SIMVA in xAPI-SG format.

T-Mon uses some common Python libraries to perform the analysis and visualizations. Apart from these, T-Mon does not require any further configuration, as all analysis and visualizations are performed and displayed automatically. This way, the tool is accessible to non-experts in the domain. Additionally, data scientists can perform further analysis in the Python Jupyter Notebooks to extend the analysis and visualizations included. T-Mon is openly and freely available on GitHub[1], to be downloaded and launched locally (Fig. 7). Additionally, T-Mon can also be launched remotely using Binder (directly from the GitHub repository). The Binder launching deals with all library dependencies and provides a web-based interface to test the tool uploading the xAPI-SG data file.

[1] https://github.com/e-ucm/t-mon

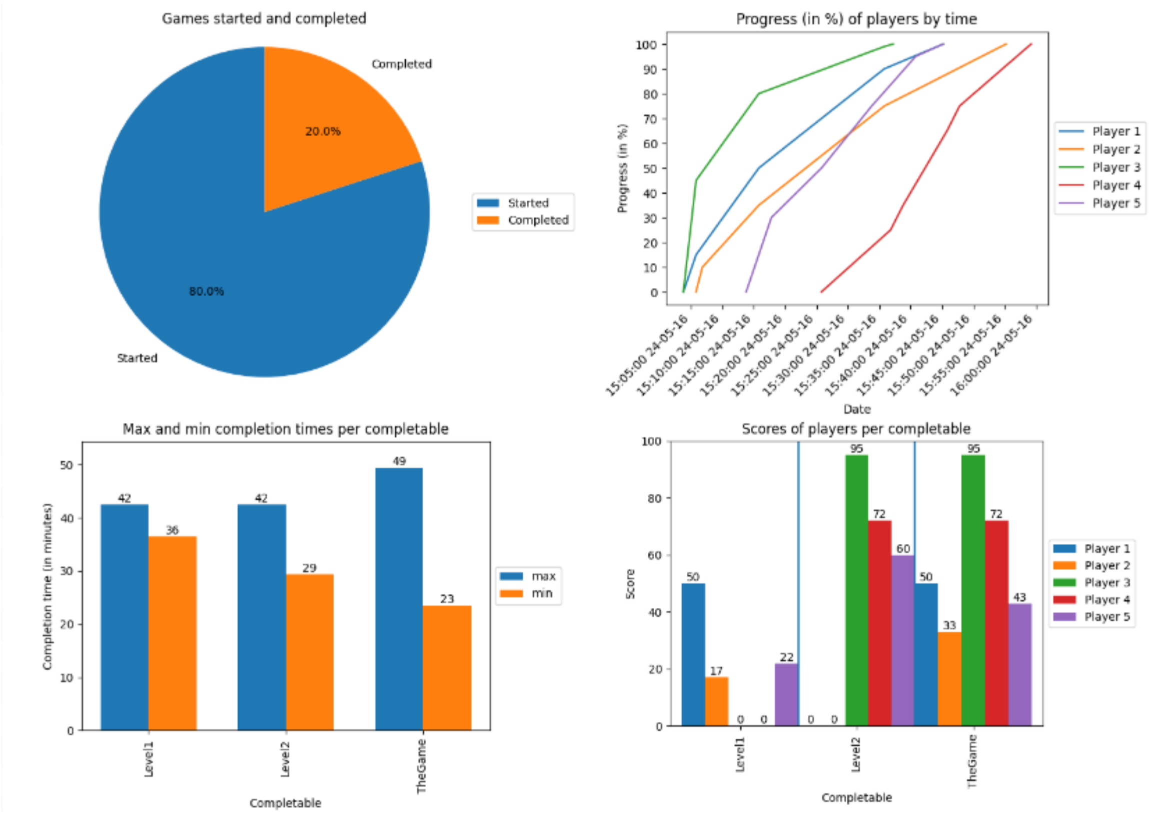

Fig. 5. Four of the default visualizations included in T-Mon (left to right, top to bottom): pie chart with percentage of serious games started and completed; line chart with progress (*y-axis*) of each player in the game over time (*x-axis*); bar chart with maximum and minimum completion times (*y-axis*) in each completable (*x-axis*), max and min times corresponding to each bar per completable; and bar chart with scores (*y-axis*) obtained by each player in each completable (*x-axis*), each bar per completable corresponding to one player.

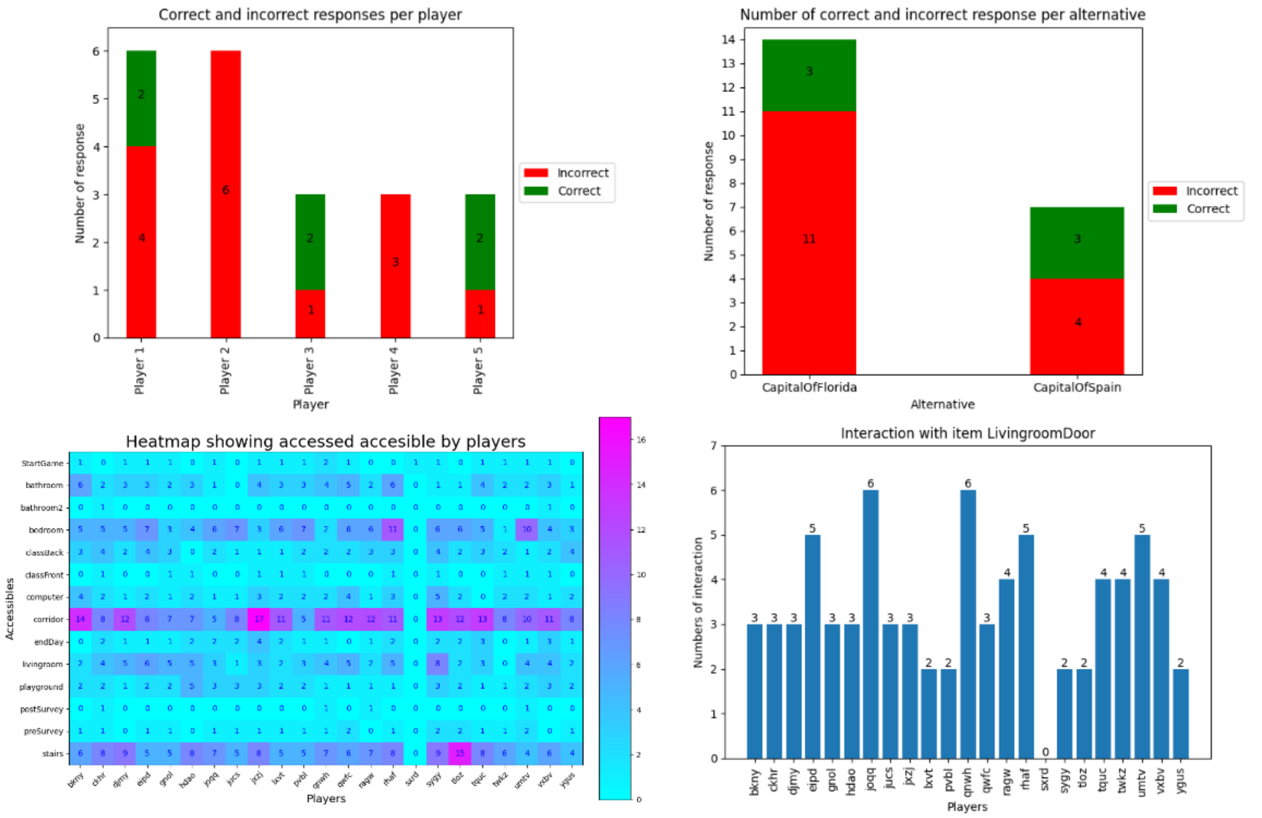

Fig. 6. Four of the default visualizations included in T-Mon (left to right, top to bottom): bar chart with correct (in green) and incorrect (in red) number of responses (*y-axis*) in alternatives per player (*x-axis*); bar chart with correct (in green) and incorrect (in red) number of responses (*y-axis*) per alternative (*x-axis*); heatmap with times each accessible (*y-axis*) has been accessed per player (*x-axis*); and bar chart with number of interactions (*y-axis*) per player (*x-axis*) with an item.

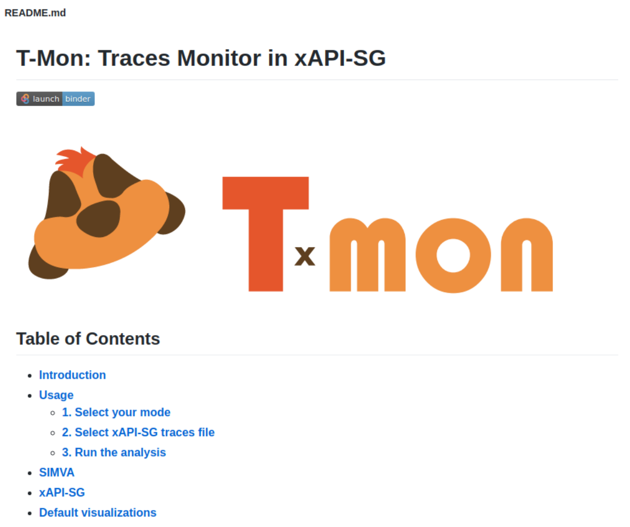

Fig. 7. T-Mon GitHub page, available at https://github.com/e-ucm/t-mon.

IV. Discussion and Conclusions

To extract information from players' interactions in serious games, the whole process needs to be considered: from the definition of the relevant interactions in the game, their collection in a specific format, and the aggregation, analysis and reporting of the information gathered. For this process to provide meaningful results, the relevant data to be collected from the games needs to be clearly defined from the very start [24]. The use of a standardized data format to collect the user interaction data and the use of a pre-defined language to represent the interactions and specific game mechanics allow the creation of tools to automate analysis, such as T-Mon. The development of tools that simplify data collection and analysis, as well as the use of standards and clearly-defined data models to integrate analytics in serious games, can ease the study, evaluation and adoption of games as educational tools, minimizing the current barriers for their adoption. These tools simplify the application of serious games for users with a less technical profile: T-Mon helps to build the minimum viable analytics, by providing a low-cost entry point to the use of game learning analytics and the validation of serious games. This could also be the case of data-science experts that have little game analytics knowledge. The use of standards is also clear benefit to simplify later analysis, and integration with other ecosystem services and tools [25]. Additionally, if allowed by the data management guidelines, the use of the standard also simplifies data sharing, providing a clear framework to understand the interaction data shared.

Once data is collected, to actually provide meaningful information to the stakeholders involved, it is useful to provide some visual display of aggregated data or results, hiding the low-level details about the analysis performed and, instead, showing meaningful summaries of gathered information. The application of tools that provide default game-independent analysis and visualizations detaches users from the details of the analysis required. This simplifies their use, as they can be adopted as a black box, and the final user does not need to know the characteristics of the collection data format or the data analysis. This is the case of the default set of analysis and visualizations provided by T-Mon. Even more so, by using the xAPI-SG standard, the reports provided can be obtained without any knowledge of the game design details, isolating the analysis and visualizations from the game design. This could benefit, among others, game experts with little knowledge of data analysis. With this features, T-Mon covers both the steps of statistics and visualizations considered in Learning Analytics models [17] as well as the reporting and visualizations (including offline) of results considered in Game Learning Analytics models [10]. All this information can be obtained remotely using the tool available online, which simplifies its application in diverse contexts, such as the ones faced currently in the New Normal after the covid-19 pandemic.

The level of detail and granularity in the result visualizations is adaptable according to the amount and characteristics of the interaction data collected. T-Mon allows simple descriptive analysis of player decisions, but also allows performing more detailed and complex default analysis. For instance, a possible lower-level analysis would entail examining in-game conversations, to determine whether players are actually taking the time to read conversation lines or simply skipping them. By collecting interaction data of the relevant actions in conversations (e.g. as accessibles or completables), T-Mon could display the information of such players' actions to see if players are skipping conversations, or how much time they are spending in them.

Additionally, T-Mon can also be used by data scientists and other technical users, who could extend and complement the default set of analysis and visualizations if needed to meet any requirements that go beyond the ones covered by default. This includes the possibility of exploring more complex data mining and machine learning techniques (e.g. for predictions) which, given knowledge about the game and learning design, could complement the default analysis to provide a more evidence-based assessment of players based on their game decisions, further extending their scope of application. For non-experts, however, the ready-to-use analysis and visualizations provide an overview of the interaction data to extract information about players' progress and process in the serious game.

T-Mon provides a default set of analysis and visualizations that can be used to report and visualize results of the interaction data collected from serious games, using the xAPI-SG standard. Data that adheres to the standard is analyzed, and all the fields and types included in the SG Profile are used in the default analysis and visualizations. T-Mon can therefore help to easily and quickly obtain an overview of the interaction data collected from the serious game. T-Mon's simple and user-friendly interface and the data standard used can further simplify integration with other systems. With this tool, and the only requirement of using the xAPI-SG standard data format, we expect to simplify the analysis and visualization of interaction data from serious games.

V. LIMITATIONS AND FUTURE WORK

The tool has some limitations: the requirement that the input data should follow the xAPI-SG standard limits its application to other types of interaction data collected. However, this standard data format is broad and flexible enough so that most serious game interactions could be tracked using this format and, therefore, be analyzed and visualized using T-Mon. The analysis and visualizations included could be further extended with two perspectives: on the one hand, providing more in-depth information about some of the specific types included in the Profile; on the other, including analysis and visualizations that are more general to xAPI information that do not meet the specifics of the xAPI-SG Profile: we plan to continue working on the tool to further extend the analysis and visualizations included.

For the moment T-Mon has so far been tested and improved with xAPI-SG data collected in several previous experiments of the research group. In the future, we will carry out new case studies with other researchers to further evaluate its usability and improve the tool.

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