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Building a specialist agent to assist in the implementation of Game Learning Analytics techniques

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Abstract. *Game Learning Analytics (GLA) involves capturing and analyzing data from educational games, enabling the identification of evidence of learning. A fundamental step before implementing GLA techniques is data modeling, which is not trivial. Using large language models (LLMs) can help in this context, as they can generate text like humans. Therefore, considering Chat-GPT and its customizable functionality, "MyGPTs," this work proposes creating a specialist agent to assist learning designers in data modeling and implementing GLA techniques based on the GLBoard system. Preliminary results with GLA specialists were positive, indicating the agent's potential.*

1. Introduction

The field of Game Learning Analytics (GLA), which deals with capturing and analyzing data from educational games, has been growing in recent years [Freire et al. 2023, Banihashem et al. 2023]. Through GLA techniques, the player's interactions with game design elements generate data records (logs), which make it possible to track their progress during the game and their decision-making in the phases. For example, time records, enemies defeated, checkpoints reached, etc. Thus, in addition to information from questionnaires and post-game assessments, there is an evidence-based approach that collects real-time data related to gameplay, enriching learning analyses [Freire et al. 2023].

Despite its benefits, GLA presents the following obstacles: (i) the complexity of implementing the techniques, which impedes developers from including them [Saveski et al. 2016]; and (ii) the lack of standardization, so that data collection is implemented only in specific contexts, and is not replicable [Alonso-Fernandez et al. 2017]. In this regard, with the aim of systematizing data capture and analysis in educational games, GLBoard [Silva et al. 2022] was proposed. This system consists of four modules that standardize the generic data to be extracted, send it to a database, perform the analyses, and display it through graphs on a web dashboard.

In this way, GLBoard allows the insertion of GLA without the need to implement a specific system, standardizing data collection in a capture structure in JSON format. This structure is divided into four main classes: $PlayerData$ (data about the player's profile), $GameData$ (data generated by the player during gameplay), $Phase$ (game phases or levels), and $Section$ (player sessions, which can be interpreted as attempts). To implement

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it, the developer must install the package via the Unity game engine and assign the corresponding variables from their code to the fields of this structure. One of these fields is the $path\_player$ variable (within $Section$), which allows storing any set of variables related to the player's path. In this way, GLBoard makes data collection more flexible by allowing the user to "customize" the $path\_player$ according to their game.

A step that precedes the implementation of GLA techniques, including the customization of the $path\_player$ in GLBoard, is data modeling (or selection). This process consists of defining which data will be relevant to capture and why they are necessary to help identify evidence of learning [Alonso-Fernández et al. 2021, Kitto et al. 2020]. For example, collecting time records can be essential to analyze how long a player takes to decide. However, this step is not trivial. Learning designers face challenges in carrying it out, such as the complex nature of building educational games, appropriation and understanding of learning mechanics, and data organization, among other factors.

A possible alternative for this scenario is the use of Large Language Models (LLMs), which, given the emergence of the area and their contributions to the field of Natural Language Processing (NLP), are capable of performing numerous tasks and generating text-like human being [Kasneci et al. 2023]. Because of this, this field is also called Generative Artificial Intelligence (GenAI) by some authors [Jovanovic and Campbell 2022]. In these models, the user interacts with a chatbot via a prompt (instructions), which returns a response from its knowledge base.

One of the most widely used models is OpenAI's Chat-GPT[1], with over 180 million monthly users and 349 related scientific publications in the Scopus database as of August 2024 [DemandSage 2024]. Starting in November 2023, OpenAI introduced the "MyGPTs" functionality, where the user can create customizable versions of Chat-GPT that combine instructions (self-description) and extra knowledge (files that can be uploaded to compose the database, such as TXT, PDFs, etc.) [OpenAI 2023]. In this way, similar to the fine-tuning process in open models (whose model code is freely made available for parameter adjustment), this option allows the customization of a model to perform specific activities. Thus, it is possible to create a conversational agent that is an specialist in a given topic without coding.

Therefore, considering the popularization of LLMs, the possibility of creating an specialist via Chat-GPT, the difficulty in modeling data for educational games, and the complexity in implementing GLA techniques, this work has as a research question: "how to create an specialist agent capable of contributing to data modeling in educational games and in the implementation of Game Learning Analytics?". Section 2 includes the theoretical foundation and related works, Section 3 presents the methodology used in the research, Section 4 displays the preliminary results and discussions, and Section 5 presents the final considerations.

2. Foundations and Related Work

When it comes to Large Language Models (LLMs), they can be categorized into two types related to their access: open (such as Meta's LLaMA) or closed (such as OpenAI's Chat-GPT, Google's Gemini, etc.). The source code is available in open models and can be

[1]https://chatgpt.com/

downloaded to adjust the weights (fine-tuning), thus training it for different contexts (personalization). In closed models, fine-tuning is not possible, and their training can be done via Prompt Engineering. This strategy involves designing the model's input instructions (prompts) to obtain the desired responses [Lo 2023].

In an attempt to systematize the numerous prompting techniques, research has proposed taxonomies and typologies [Liu et al. 2023, Sahoo et al. 2024]. However, given the area's emergence, many new techniques emerge for different contexts, making standardization difficult. Furthermore, designing prompts is not a trivial activity. Therefore, the "MyGPTs" functionality is a good alternative for this scenario, as it facilitates the customization of models and does not require the coding or elaboration of complex prompts. Below are some related works identified in the literature that propose specialist agents that use this Chat-GPT option.

The work of Almasre [2024] sought to investigate how Chat-GPT can be used to evaluate activities submitted by students in a typography course and compare their evaluations with those of human evaluators. The "Typography Evaluator" tool was built using the customizable feature of Chat-GPT, whose performance was evaluated through mixed methods, considering text classification and feedback. The results indicated a statistically significant difference between the evaluations of the AI tool and those of Evaluator 2; conversely, none is shown when compared to that of Evaluator 1.

Similarly, Kiyak and Kononowicz [2024] created the "Case-based MCQ Generator", a custom GPT for generating high-quality, clinically relevant multiple-choice questions. The tool simplifies question creation by integrating prompts from the medical education literature, avoiding the generic and time-consuming copy/paste process of standard Chat-GPT prompts: clinicians choose a prompt and provide input details (learning objective, topic, etc.) and then obtain contextual, relevant questions. Future work includes creating a support ecosystem around the tool and sharing it in an accessible way.

In Sathe et al. [2024], the authors describe their experiences building AI chatbots (customizable GPTs) for thematic analysis, research design, curriculum creation based on Kern's six steps, simulation of training exam questions, etc. In addition, a customized GPT was designed for surgical education. Overall, the chatbots were promising but had some limitations; for example, they referenced relevant information from the knowledge base but often provided advanced information to the user, which was not requested. Based on some analyses of the advantages and disadvantages of its use, the authors conclude that, despite the risks, generative AI has the potential to be a democratizing technology in surgical education.

From literature searches to find similar works, mainly in the Scopus database with different search strings, it was noticed that there are few works that: (i) address agents created in Chat-GPT with the "MyGPTs" option, since the functionality is relatively new (less than a year old), most of which refer to the health area; (ii) contemplate adjusted models focused on games – some focus on generating missions, dialogues, and arguments, but do not refer to a specialist agent; (iii) involve Large Language Models for Game Learning Analytics. Therefore, the difference between this research and related works is the proposal of a specialist agent using the "MyGPTs" option of Chat-GPT to assist in implementing Game Learning Analytics.

3. Methods

An interactive-incremental methodology was chosen to build an agent specialized in Game Learning Analytics (GLA) to add new modifications to the system based on inconsistencies identified in tests, which links theory and practice: Design-Based Research (DBR). DBR was proposed around 1992 by Ann L. Brown and Allan Collins and consists of iterative cycles of design, analysis, and implementation, which begin after the definition of the requirements and theories raised [Brown 1992, Gagnon and Barber 2018, Reimann 2011, Fraefel 2014], as illustrated in Figure 1.

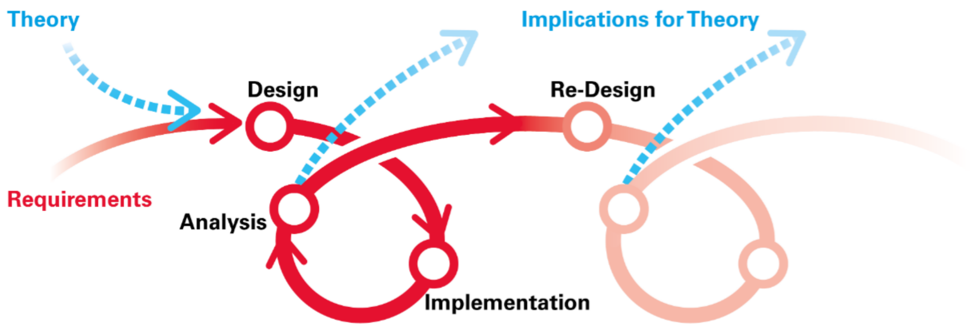

Figure 1. Stages of Design-Based Research (DBR), by Fraefel [2014].

Theory and Requirements: the theoretical basis for constructing the Game Learning Analytics specialist agent comes from the analyses carried out in related works in the literature (described in Section 2), which propose customized GPTs for specific contexts. Creating a customizable chatbot can be beneficial by avoiding the generalization of the standard Chat-GPT, allowing the inclusion of a particular database, and not requiring coding to adjust the model or design complex prompts. Regarding the requirements, both for data modeling and for the implementation of GLA techniques, they are based on the functionalities of GLBoard since it is a free tool, with documentation available online and that standardizes data capture in a JSON format structure – and can be customized for any educational game.

Design: the specialist agent was designed by the authors of this work, who have experience in building educational games and gamification, as well as in *Learning Analytics* and *Game Learning Analytics*. The first step was to access the "MyGPTs" option in Chat-GPT – available in the Plus version for a fee – and configure the agent in the area called "GPTBuilder". Within it, there are two tabs: "Create", to define the agent's functionalities via conversation with the chatbot, and "Configure", which has specific fields to determine the agent's properties (name, description, instructions, icebreakers[2], knowledge, capabilities, and actions). Therefore, using the options, the agent's name was defined as "GLA Specialist, " and the other information was added after.

Implementation: this step refers to selecting works to compose the agent's database. Initially, using the "Google Scholar" tool, the most relevant works that address *Game Learning Analytics* were identified in the literature, whose selection criterion was to be indexed in the first pages of the Google database. In addition, the article referring to

[2]Direct messages that the user can click to help start a conversation.

the proposal of the GLBoard tool, its documentation, and a JSON schema that represents the data capture structure used in the system were selected. This material was downloaded and incorporated into the agent's "Knowledge" in TXT, PDF, and PNG formats.

Analysis: to identify inconsistencies in the agent, tests were conducted in the "Preview" area, which allows interaction with the chatbot before sharing it. These tests included general questions about GLA and GLBoard, requests to assist in implementing techniques, requests to generate data capture structures from information about certain educational games, etc. Among the reservations noted, the following stand out: the proposal of data capture structures unsuitable for GLBoard (format, logic, etc.), failure to perform some requested steps, etc. With this, it was possible to proceed to the next stage.

Re-design: in this step, the agent is improved by fixing previously identified inconsistencies. These adjustments were made by updating the agent's self-description, such as (i) adding a step to ask the user if the agent can ask questions about the educational game provided, (ii) emphasizing the customization of structures by the specialist, (iii) mentioning creators for historical context; (iv) a more detailed explanation of the $path\_player$ variable, responsible for storing information related to the player's path during the phases, among others. The agent's current self-description can be viewed in link[3].

Test Application: after the cyclical process of adjustments and analyses, a point was reached where the agent's responses were satisfactory. This validation took place in the "Analysis" stage by the authors of the work – also specialists in GLA – who used exploratory tests to analyze the agent's responses. Therefore, using the "Share" option, the agent was sent and tested by seven GLA specialists. The tests were conducted online, with the testers using a test script[4] to guide the experiment, but not limited to it. Data was collected via a Google Forms questionnaire, with qualitative and quantitative questions about the tester's profile and the agent (covered in Section 4). Quantitative data were analyzed through histograms, while qualitative data were analyzed through content analysis [Bardin 2015]. The results of these analyses are described in Section 4.

4. Preliminary results and discussions

After the iterative-incremental process of the DBR methodology, the preliminary version of the "GLA Specialist" artifact was finalized: a Game Learning Analytics specialist agent with an emphasis on GLBoard. Among its attributions, the agent: (i) assists in the understanding of Game Learning Analytics and the GLBoard tool; (ii) collects information about educational games to propose capture structures; (iii) asks questions about the educational game, if authorized by the user, to improve the structure; (iv) customizes the structure based on information from the games and questions, including variable names and their data types; (v) includes comments in the structures to understand the data modeling; (vi) generates an example of a JSON structure to illustrate the values that the variables can store; (vii) validates the generated structure with the user, enabling modifications; and (viii) focuses on proposing sets of variables to replace $path\_player$, storing the player's path. Figure 2 illustrates the agent's response when informing an educational game's characteristics. This extended interaction can be consulted in this link[5].

[3] https://drive.google.com/file/d/1ueHqpWq6UmrAwAFbsrmTECTbKOFHzp45/view?usp=sharing
[4] https://drive.google.com/file/d/1yC6NBppvJOmNsfnPuSMfDvtrAg9obP2N/view?usp=sharing
[5] https://drive.google.com/file/d/15OHqeRGGoiuv1QB3e5Enfb-NutZmpU7p/view?usp=sharing

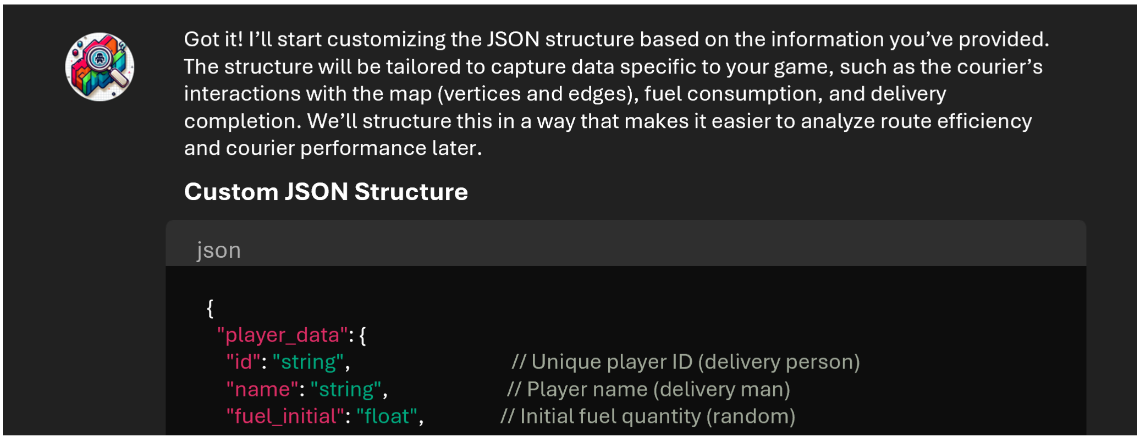

Figure 2. JSON structure generation by the specialist agent.

Seven GLA specialists were invited to participate in the evaluation regarding the agent testing. The profile characteristics of these specialists are: (i) education: 43% with a degree in computing courses in progress, 43% starting a master's degree in informatics or progress, and 14% with a doctorate in progress; (ii) experience in game development: 86% with two years or more and 14% with one year; (iii) experience in GLA: 57% with less than one year and 43% between 1 and 3 years; and (iv) number of games in which implemented GLA: 71% for one game and 29% for none or two games.

Table 1 illustrates the specialists' evaluations of the agent, collected via a questionnaire on Google Forms. The scores for the qualitative questions range from 1 (completely disagree) to 5 (completely agree) on a Likert scale, and the histograms for each question can be found at link[6]. In general, the results were positive: all evaluators assigned scores of 4 (agree) or 5 (completely agree) to the questions – for this reason, scores from 1 to 3 were omitted from the table – with an average higher than 4.4 and medians of 4 or 5, expressing the agent's potential and mastery of GLA and the GLBoard tool.

Table 1. Distribution of Scores per Question

Question	Description	Score 4	Score 5	Mean	Median
Q1	Did the agent provide accurate and relevant answers to your questions about GLA?	29%	71%	4.71	5.0
Q2	Did the agent provide accurate and relevant answers to your questions about GLBoard?	43%	57%	4.57	5.0
Q3	Was the agent able to customize the JSON structure based on the information provided about your educational game?	57%	43%	4.43	4.0
Q4	Did the agent adequately explain the variables proposed in the path_player?	29%	71%	4.71	5.0
Q5	In your perception, were the examples that the agent generated adequate to capture information about GLA data and technical implementation?	71%	29%	4.29	4.0
Q6	Do you think the agent has the potential to assist in data modeling and implementing GLA techniques?	29%	71%	4.71	5.0
Q7	How would you rate your overall experience interacting with the "GLA Specialist"?	86%	14%	4.57	5.0

Regarding the qualitative questions, open-ended questions were asked to collect feedback from the evaluators: **Q1)** What did you like most about the agent? **Q2)** What did you not like about the agent? **Q3)** What improvements would you suggest to improve

[6]https://drive.google.com/file/d/15d5kBkVi9HQlo7h6dJSscPmgqGtTYlzq/view?usp=sharing

the "GLA Specialist"? **Q4)** Was there anything the agent could not do or respond to as expected? If so, please explain. **Q5)** Do you think the agent is a good option to help students understand/implement GLA? Why?

Regarding **Q1**, the evaluators pointed out that what they liked most about the agent were the precise answers, the specific questions to understand the game, the ease of generating the capture structure with only the game information, the practicality in reducing the complexity of structuring the JSON and suggestions of graphs to interpret it. In **Q2**, some evaluators pointed out that there was nothing they didn't like about the agent. In contrast, others indicated that they didn't like very long answers, lack of examples of applications and existing technologies, length of the JSON, and suggestion of complex variables to be captured. Regarding **Q3**, some specialists did not suggest improvements. In contrast, others suggested examples with images, submission of game documentation to obtain more precise answers, addition of more examples in JSON for the agent, and providing more compact answers. In **Q4**, most of the answers were "no", but one evaluator indicated curiosity in implementing the structure in the game, sending the data collected from the players and seeing how the agent would improve the structure. Another pointed out that the agent did not fully understand the game to provide the structure, but it indicated introductory steps for data modeling. The responses to **Q5** were unanimous: all evaluators agreed that the agent was a good option to assist in understanding and implementing GLA. Among the reasons, the following stand out: precise answers on the subject, assistance in data modeling, time optimization, and examples of structures.

Overall, the agent was well evaluated by GLA specialists, both in quantitative and qualitative questions. Minor caveats were identified, such as long responses, complexity of some proposed variables, and JSON size, which will be considered for further agent improvement. Suggestions will also be considered in the future version of the agent, such as requesting game documentation, adding more examples of structures to the agent's knowledge base, asking the user to choose long or compact responses, etc. These results express the agent's potential to assist in data modeling and implementation of GLA techniques, providing a simple conversational environment that does not require the elaboration of complex prompts and with a specific knowledge base that can be improved.

The limitations of this research includes: (i) the bias of GLA specialists, who belong to the same research group, which may have affected the integrity of the evaluations; (ii) the analysis of the study, since it only contemplates the perspective of specialists (not yet of students) about the use of the agent; (iii) the tests conducted, which superficially analyze the agent's responses, not performing a statistical comparison with other strategies (Chat-GPT's versions, other LLMs, etc.); (iv) the emphasis on GLBoard, whose agent proposes structures compatible with this model but not with other tools – such as x-API-SG [Alonso-Fernández et al. 2021, Serrano-Laguna et al. 2017]. As an initial study, this work aimed to present the first steps towards building a GLA specialist agent, focusing on analyzing the perspective of GLA specialists when using it and not yet comparing the generated structures, whose limitations will be minimized in subsequent works.

5. Conclusion

GLA techniques can help identify evidence of student learning, which can be implemented in tools such as GLBoard. However, a step before this implementation is considered challenging by learning designers: data modeling, which consists of defining which data will be collected and why they are relevant to express the player's evolution. LLMs can be an alternative to minimize this difficulty due to their ability to perform numerous activities and generate texts like human beings, such as OpenAI's Chat-GPT. This model contains a functionality called "MyGPTs" to customize a conversational agent (chatbot) for specific activities without coding.

In this scenario, this work presented the following research question: "How to create an specialist agent capable of contributing to data modeling in educational games and to the implementation of GLA?". To achieve this, it was necessary to use an iterative-incremental methodology such as Design-Based Research (DBR), which included the following stages: (i) theory and requirements, analyzing related works in the literature on customizable agents and verifying their benefits, in addition to eliciting requirements based on the functionalities of the GLBoard system; (ii) design: the creation of the specialist agent via "MyGPTs" from Chat-GPT, adding its properties such as name, description and instructions; (iii) implementation: selection and incorporation of works on GLA and material from GLBoard to compose the agent's knowledge base; (iv) analysis: tests to identify inconsistencies in the model during its production; (v) redesign: adjustments to the model's self-description based on the reservations in the previous stage; and (vi) application of tests: after the various iterations of the process, tests with GLA specialists to analyze the agent's performance and potential.

As a result, the "GLA Specialist" agent was designed, and its primary goal is to assist in understanding and implementing Game Learning Analytics techniques based on the GLBoard tool. One of the agents' functions is to collect information from the users' educational games and ask them about it, if authorized, by generating a structure in JSON format (GLBoard standard) to capture data in the respective games. Positive results were obtained from the preliminary evaluations with seven GLA specialists. In the quantitative questions to analyze the agent's performance, potential, and experience, all specialists gave it grades of agreement (4 and 5). Regarding the qualitative questions, the specialists liked the agent's precision, ease, and practicality, highlighting some suggestions such as examples with images, sending the game documentation, and adding more examples of structures to the agent's knowledge base. Some reservations were also identified, such as long answers, complex capture variables, and the absence of more examples of existing applications/technologies.

Therefore, the specialists' evaluations indicate the agent's potential to assist in data modeling and implementation of GLA techniques, emphasizing GLBoard. Considering this to be introductory research, the focus was initially on analyzing the agent with GLA specialists to validate him and identify inconsistencies to correct them in the later version. In this regard, future work includes (i) making adjustments to improve the agent based on the specialists' feedback, (ii) using the agent with students and developers (learning designers), comparing the structures generated by other strategies (Chat-GPT versions and manual mode), aiming to confirm whether the agent produces more appropriate structures; (iii) including support for implementing GLA techniques in other tools, such as x-API-SG; and (iv) enabling free access to the tool, since Chat-GPT Plus (paid version) is required to use it.

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