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SAGE: A dataset for Smart Adaptive Gamified Education

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Abstract. *Gamification design in education is the process of planning gamification strategies aligned with educational needs. However, the literature states that generating those strategies is not trivial, and it requires a lot of effort from gamification designers and educators due to the large number of game elements, especially since some of these elements are defined in confusing or misleading ways, context specificities in the teaching-learning processes, and the interaction between them. Based on this premise, this paper presents the design and data collection of a dataset composed of 1929 items (line entries in the dataset). This dataset was made through a survey data that went through a data filtering process and can be used to support tailored gamified tools or AI-based tools (e.g., recommendation systems) for educational environments, based on students' profiles and favorite game elements.*

1. Introduction

Gamification is defined as the use of game-like elements outside of a game, focusing on specific purposes related to users' motivation and engagement [Deterding et al. 2011]. The use of gamified strategies in the educational domain and how to adapt these elements to different contexts has gained attention in the last five years [Rodrigues et al. 2020, Klock et al. 2020] since gamification aims to improve educational processes [Bai et al. 2020].

However, generating these strategies is not a trivial task, which is why the field of gamification design focuses on understanding ways to mix game elements to create meaningful experiences [Palomino et al. 2020]. Recent works on this topic have focused on addressing this challenge by proposing systematic guidelines on how to use these elements [Mora et al. 2017], while lacking precise instructions on how such elements can be interrelated. So far, studies did not supply any actual dataset that provides evidence on why a given game element (or group of game elements) is suggested to specific students within the educational context, which prevents further enhanced decision-making processes of gamification designers and educators through emerging Artificial Intelligence (AI) algorithms [Meder et al. 2017].

In this sense, this paper aims to presenting and providing a dataset called SAGE which can be used alongside unsupervised and supervised learning to generate possible gamified strategies, supporting gamification designers and educators, as well as serve as the basis for AI tools that facilitates the automated generation of those strategies [Rodrigues et al. 2023]. Thus, this work contributes to the field of data-driven gamification design which uses AI algorithms to facilitate the decision-making process for educators, and instructional and gamification designers towards improving students' experience [Meder et al. 2017]. Based on real data, these strategies can be tailored to promote a better learning environment for learners and educational actors (e.g., teachers and lecturers), since such tailoring approaches tend to promote positive learning outcomes [Klock et al. 2020].

2. Related work

Datasets on gamification are scarce, especially in the education domain. Most studies do not make the datasets available, except for published papers and already processed data. Even Kaggle, an online repository that aggregates datasets used for business or academic purposes, has only 1 dataset regarding gamification in education[1].

When investigating the proceedings of the Brazilian Conference on Computers in Education[2], for instance, the work of [Palomino et al. 2019] analysed gamified strategies through the lenses of data mining algorithms (more specifically, through association rule mining). In their work, the authors found possible associations between some game elements of a given taxonomy (e.g., progression, cooperation) and narrative and storytelling. They analysed the perspective of Brazilian gamers, and identified some strategies that could be useful when tying narrative and storytelling to other game elements. In this work, the data that was presented was the perceived relevance of game elements through a Likert scale from 1 to 5 (where 1 was not relevant, and 5 was very relevant). It is important to note that the dataset was not present in the published study.

Another study that provided a public dataset is the TWOS, constructed by [Harilal et al. 2018], where the authors presented the dataset of a cyber security competition involving gamification. The dataset contained data regarding the monitoring of the competition based on activity logs, psychological questionnaires, different kinds of logs, and network traces. The authors explained how the data can be used and which kinds of analyses can be made through their dataset.

In addition, [De-Marcos et al. 2016] published a dataset based on their research regarding the comparison of gamification, gaming, and social networking in a learning

[1] Search made on May, 23th 2023

[2] Available in the SOL Open Library

context. In this case, the data was made available alongside the research paper that it was based on, which means that most of the possible analyses were carried out up to that point.

Considering our related work, only two of them [Harilal et al. 2018, De-Marcos et al. 2016] provided the dataset of their study, and only one of these [Harilal et al. 2018] had possible research directions on how to use and analyse the data contained within. Although the study of [Palomino et al. 2019] provided some interesting insights on the use of unsupervised learning algorithms to find patterns within the data, the dataset itself was not present in the study, alongside possible guidelines on how the analyses can be made. Thus, our dataset can provide enriching data to the field of data-driven gamification design, especially when considering the generation of automatic strategies using AI algorithms to support educational actors.

3. Methods and tools

To produce the dataset, a data-driven, 'bottom-up' approach to gamification design, starting from the stated preferences of learners to their perceived importance of game elements was used. To collect the perceived importance of game elements, we use a taxonomy designed for educational purposes [Toda et al. 2019]. We opted to use this taxonomy due to its classification based on existing literature reviews and gamification studies. Based on this premise, we infer that the elements contained within this taxonomy might be coherent to describe game elements in educational contexts.

To collect this data, we opted for designing and applying a survey[3], since this method allows acquiring many answers at a low cost [Lazar et al. 2017]. The survey took the appropriate ethical and privacy precautions, aligned with the General Data Protection Law[4] and General Data Protection Regulation[5], including explanations of research goals (i.e., about selecting gamification constructs they would prefer to see in an educational context) and data usage (for scientific purpose). The survey was divided into three groups of data: demographic data, gaming experience, and gamification preferences. We also applied the Informed Consent Form, so the respondents agreed on sharing their information.

We collected respondents' gender, age, and country, as well as personal information related to their gamification contexts, such as the experience of playing games (in years), hours per week of playing games, favourite game genre and game setting (i.e., multiplayer or singleplayer games). Since tailored gamification is considered important for obtaining, overall, positive tendencies in learning environments [Bai et al. 2020], it is important to collect well-refined and grained data to allow the adaptation and personalisation of gamification strategies. Since an early study conducted by [Toda et al. 2020] revealed that the gaming profile could have an overall positive tendency towards accepting gamification, we believe that the learners' experience with gaming (years playing, hours per week, favourite genre, and setting) can influence in the strategies that can be generated.

We then collected the perceived importance of the 21 different game elements presented in the [Toda et al. 2019] taxonomy. Any other personal data that could directly

[3]It is important to note that the survey was designed in English to reach a higher global sample
[4]https://www.gov.br/mds/pt-br/acesso-a-informacao/lgpd
[5]https://gdpr-info.eu/

identify the users was not collected. A brief description of each collected data can be seen on Table 1.

Table 1. Collected data

Group	Data	Description	Type of input
Demographic	Gender	Surveyees' gender	Text (open form)
Demographic	Age	Surveyees' age	Number
Demographic	Country	Surveyees' country of residence	Text (open form)
Gaming experience	Experience (in years)	The amount of years surveyees have been playing games	Number <Age
Gaming experience	Hours (per week)	The amount of hours the surveyee spends per week on playing games	Number <168
Gaming experience	Favourite genre	The surveyees' favourite game genre (only considered one)	Text (open form)
Gaming experience	Favourite game setting	The surveyees' favourite game setting (between single and multiplayer)	Radio button
Gamification preferences	Importance of <element>	The surveyees' perceived importance of a given game element that was presented to them during the survey. This question analysed each of the 21 elements of Toda et al taxonomy[Toda et al. 2019].	Likert scale from 1 to 5

Following, we conducted a data filtering process, in this step, the following criteria were defined, to filter the data and remove outliers: (a) gender that did not conform according to [Spiel et al. 2019] was filtered out (e.g., people who identified themselves using random words, e.g., ”Egg”); (b) invalid age was removed (e.g., people declaring themselves older than 100 years); (c) people whose experience surpassed the defined age (e.g., people who said they were 20 years old, but had 24 years of experience in playing, or people that had the same age in the years playing as experience); (d) people who inserted an impossible number of hours played per week (e.g., more than 168 hours).

After removing outliers and before the analysis phase, the data collected was further standardised. Firstly, five age groups (A to E, from 10 to 10) were created: A) < 15; B) 15 - 24; C) 25 - 34; D) 35 - 44; and E) $>= 45$. It is important to note that we also made available the raw data, before standardisation, so future studies can make analyses through the raw values instead of grouping them. We also classified the favourite game genres of the respondents, using established classifications proposed by the Entertainment Software Association (ESA)[6], as presented in Table 2. The games that were not similar to this original ESA classification were then reexamined by at least two experts[7] in the field, to help mapping them correctly to ESA (e.g., a game genre ”Japanese RPG” would

[6] ESA focuses on collecting data about the video-game market in the US which is also used as basis in other countries.

[7] Here, experts were selected based on their experience and interaction with games, having attested at least 10 years in both experience and interaction.

be classified as ”RPG”, and a ”MOBA” - Multiplayer Online Battle Arena - would be classified as ”Strategy”, which is the larger genre to which this type of game belongs). If the experts did not agree on a classification, a third expert would be consulted, to cast a majority vote on one of the classification discrepancies. Thus, the 66 genres identified in the raw data were reduced to 13 game genres, as in Table 2. Again, the original genres that were used as inputs were preserved so future work can further propose other ways to classify this data, we opted to conduct this step to support the creation of grained strategies with the algorihtms present in subsection 4.2 .

Table 2. Extended ESA game genres preferred by respondents in the survey

Game Genre	Definition
Action	Emphasises physical challenges, including hand-eye coordination and reaction time.
Adventure	Player assumes the role of a protagonist in an interactive story driven by exploration and puzzle-solving.
Board Games	Based on real board games.
Card Games	Based on real card games.
Casual	Allows gameplay during short bursts, matching games, resource management, puzzles, wordplay, or mobile games in general.
Fighting	Based on interpersonal combat between a limited amount of characters, in which they fight until they defeat their opponents, or the timer expires.
RPG	The player controls the actions of a character (and several party members) immersed in some well-defined world.
Racing	Attempts to provide the player with a realistic interpretation of operating various kinds of vehicles.
Rhythm	Uses rhythm and audio waves to influence the mechanics and dynamics of the game.
Simulation	Designed to closely simulate real-world activities.
Sports	Practice or adaptation of sports.
Strategy	Focuses on skilful thinking and planning to achieve victory.
Other	Game genres that could not be classified into any of the categories above, or have more than one genre.

Considering the data collection, the respondents of our survey were recruited from Amazon Mechanical Turk, since this is an accepted method of gathering users' answers, frequently used, including in recent studies [Bentley et al. 2020]. According to [Bentley et al. 2020], MTurk allows the screening of profiles and also a general and wide sample of answers, that can be collected in an organised way. In addition, further respondents were recruited via social media (Facebook, Twitter, Reddit, and Whatsapp groups), based on convenience sampling. Our target population were people who play games, whilst at the same time having some level of education and thus some expectations from education as consumers. For the latter requirement, we note that all people have been exposed to some level of education, as well as being lifelong learners, and thus having preferences regarding education. For the former requirement, opinions on game elements are only useful from those who have used them in the past in some form. These expectations were explained to respondents. To ensure our final result set contained only the target population, we further filtered the responses based on these criteria. To allow a full breadth of opinions, the data collection process was open for approximately two months, from the last quarter of January/2019 to the second quarter of March/2019. For a statistically significant sample of learners, considering the world population at 7.9 bil[8] as an upper bound of the number of learners, the minimal sample size is 384[9].

4. Results and Discussions

In this section, we present a summary of the collected data (before and after the filtering process), as well as possible research directions on how this data can be analysed by future works. The full dataset can be found in `https://github.com/ArmandoToda/Paper_SBIE2023/blob/main/DATA.xlsx`.

4.1. Summary of the data

From the total of 1929 answers obtained during the collection period, 1912 met the criteria defined in the filtering process. A tau-equivalent reliability test used to verify the answers rendered a Cronbach's coefficient $\alpha = 0.83$, meaning that there is a good consistency of the questions [Tavakol and Dennick 2011]. Concerning the demographic distributions, most of the respondents identified themselves as male (67.3%), followed by those who answered female (32%), as shown in Table 3. The majority of the sample is between 25 and 34 years old (Group C, 39.8%) and between 15 and 24 years old (Group B, 37.6%), while the average age is of almost 29 years ($\bar{x} = 28.9$, $Q_0 = 10$, $Q_4 = 77$) - see Table 3. Also, we identified 61 different countries that had respondents in this survey (the surveyees were asked which country they were from), most of them were from the United States (45.8%), followed by Brazil (22.5%) and the United Kingdom (6.7%)[10].

Table 3. Demographic data

Gender	Answers
Female	612
Male	1286
Trans	13
Prefer not to disclose	1

Age group	Answers
A (<15)	9
B (15 - 24)	719
C (25 - 34)	762
D (35 - 44)	282
E (>44)	140

Concerning the game demographics, the average gaming experience was 17.8 years (SD = 8.2) and ranging between 1 and 67 years (no fractioned values), with the median being 17. As for hours spent playing games per week, the average is 14 hours (SD = 13.3) but ranging 1 and 100 hours (again, no fractioned values), where the median was 10. Most respondents from our sample preferred single-player environments rather than multi-player ones (1336 > 576). Finally, the top 5 genres from Table 2 comprised *RPG* (735, 38.4%), *Adventure* (391, 20.4%), *Strategy* (266, 13.9%), *Action* (219, 11.5%) and *Simulation* (79, 4.1%), as seen in Table 4.

As for the game elements, Table 5 presents a summary of the mean, standard deviation, and count for each ranking, where 1 means "Totally unimportant", 2 means "Unimportant", 3 is "Indifferent", 4 is "Important" and 5 "Totally important". In this analysis, we can observe that the elements that are predominantly rejected (50% or more of the

[8]https://www.worldometers.info/world-population/
[9]https://www.surveysystem.com/sscalc.htm
[10]The complete list of countries can be seen within the dataset.

Table 4. Game genres

Game genres	Responses
RPG	735
Adventure	391
Strategy	266
Action	219
Simulation	79
Fighting	63
Sports	60
Racing	48
Casual	35
Other	6
Card games	5
Rhythm	3
Board games	3

rejections) are *Social Pressure* (53.9%) and *Time Pressure* (50.1%). On the other hand, we can see that *Progression* (85.8%), *Objectives* (81.7%), *Storytelling* (75.6%), *Narrative* (74.6%), and *Sensation* (71.9%) are those with the most positive answers, where respondents consider these elements as "Important" or "Totally Important".

Table 5. Game elements descriptive statistics. From 1 to 5 are the answers on the Likert scale to that element.

	General		Rank									
	Avg	SD	1	%	2	%	3	%	4	%	5	%
Acknowledgement	3.5	1.2	142	7.4	269	14.1	465	24.3	615	**32.2**	421	22.0
Chance	3	1.2	211	11.0	399	20.9	628	**32.8**	452	23.6	222	11.6
Competition	3.1	1.3	288	15.1	366	19.1	453	**23.7**	446	23.3	359	18.8
Cooperation	3.4	1.2	164	8.6	300	15.7	509	26.6	561	**29.3**	378	19.8
Economy	3.1	1.3	248	13.0	368	19.2	503	**26.3**	494	25.8	299	15.6
Imposed Choice	3.2	1.1	144	7.5	351	18.4	669	**35.0**	550	28.8	198	10.4
Level	3.8	1.1	57	3.0	170	8.9	433	22.6	636	**33.3**	616	32.2
Narrative	4.1	1.1	58	3	130	6.8	298	15.6	572	29.9	854	**44.7**
Novelty	3.8	1	51	2.7	167	8.7	461	24.1	736	**38.5**	497	26.0
Objectives	4.2	0.9	19	1.0	70	3.7	261	13.7	699	36.6	863	**45.1**
Point	3.3	1.2	188	9.8	346	18.1	472	24.7	535	**28.0**	371	19.4
Progression	4.3	0.8	15	0.8	57	3.0	199	10.4	689	36.0	952	**49.8**
Puzzles	3.7	1.1	62	3.2	209	10.9	488	25.5	613	**32.1**	540	28.2
Rarity	3.2	1.2	171	8.9	361	18.9	513	26.8	561	**29.3**	306	16.0
Renovation	3.5	1.1	86	4.5	264	13.8	567	29.7	653	**34.2**	342	17.9
Reputation	3.1	1.2	239	12.5	368	19.2	549	**28.7**	512	26.8	244	12.8
Sensation	4	1	51	2.7	129	6.7	357	18.7	664	34.7	711	**37.2**
Social Pressure	2.5	1.2	520	**27.2**	510	26.7	451	23.6	291	15.2	140	7.3
Stats	3.8	1.1	59	3.1	162	8.5	420	22.0	671	**35.1**	600	31.4
Storytelling	4.1	1.1	53	2.8	107	5.6	287	15.0	522	27.3	943	**49.3**
Time Pressure	2.6	1.2	429	22.4	529	**27.7**	482	25.2	322	16.8	150	7.8

Using Pearson's correlation coefficient, we identified that *Narrative* and *Storytelling* were mildly correlated ($\rho = 0.64$). We also found that *Social* and *Time pressure* are weakly correlated to *Competition* ($\rho = 0.4$), which is also weakly correlated to *Points* ($\rho = 0.39$) and *Reputation* ($\rho = 0.33$). The full correlation matrix can be seen in Figure 1.

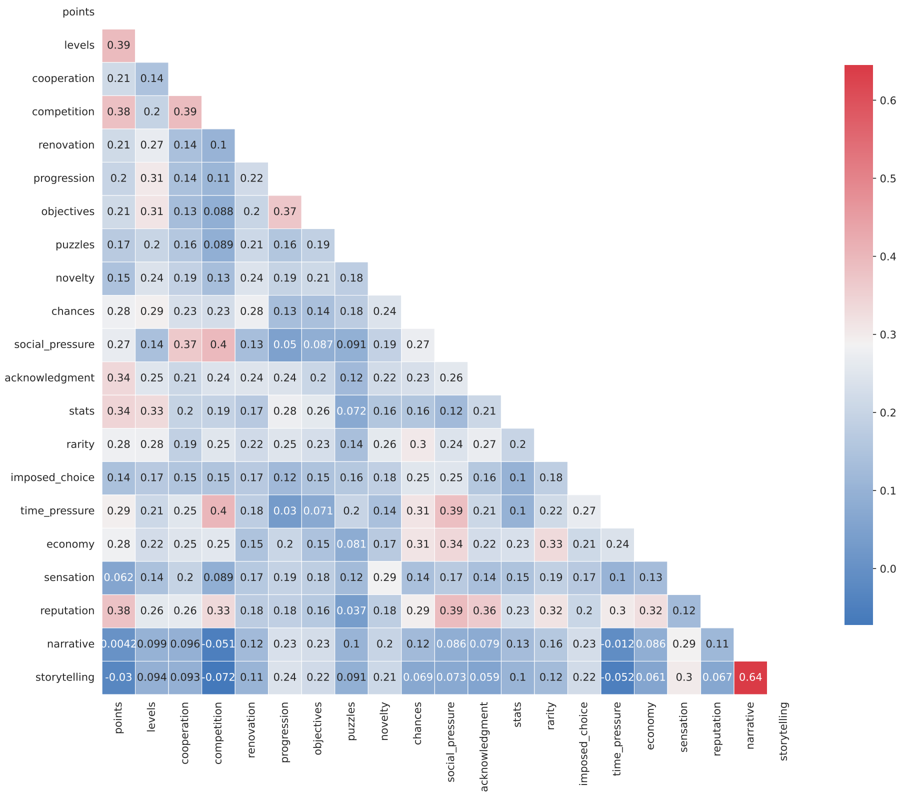

Figure 1. Correlation matrix of the student preferences for game elements

Concerning the remaining variables present in Figure 1, they present a weak or almost non-existent correlation, which means most of them are independent of each other in terms of how they are liked by our respondents. Although it is important to note that strong or weak correlation does not represent a causal effect, which means that even though these elements may appear weak or strongly correlated, it is still important to run experiments to verify if their associations might lead to positive motivation and engagement, when gamifying educational contexts.

4.2. Research possibilities

Regarding the uses of the dataset, it can be analysed with unsupervised learning algorithms such as clustering and association rule mining. Through clustering, it is possible to create profiles using demographics, gaming experience, and gamification preferences to generate strategies for specific groups. It is also possible to use association rule mining to find associations between elements, similar to what was conducted in [Palomino et al. 2019].

Besides, the country information can be used to infer or analyse different cultural aspects based on the country of residence of the surveyee. Strategies based on culture can be used in different cultural settings to understand how geographic-based culture may influence in learners' performance. When analysing the preferences through cultural lenses, it would be possible as well to anaylyse beyond the roles of gender and promote inclusive and equal gamified strategies aiming to a more meaningful experience to different learners [Cordova et al. 2022].

Another possibility is to create possible profiles based on time spent (per week) and experience in gaming (in years), as well as the surveyee's favourite game genre, to establish new types of profiles (e.g., casual or hardcore players) that could possibly influence in their perceived importance of game elements.

In addition, another possibility of use of this dataset is to use supervised learning (e.g., linear regression) to understand which aspects influence in the positive or negative perceived importance of a given game element, based on the learners' demographics and gaming experience. In this sense, this dataset can complement the previous profiling research of [Toda et al. 2020] by adding new information.

Furthermore, it is possible to increment the dataset with new data, by applying the same survey in different regions and using the same filtering process presented in this paper. It is also important to note that other types of filtering can be made, using more robust algorithms such as text mining to identify new game genres that can be used to create more grained gaming profiles (e.g., the difference between people who preffer Japanese RPGs over traditional RPGs).

5. Conclusion

This work presented the SAGE dataset which can support smartly tailored gamification. SAGE is composed of 1929 raw data divided into 28 variables (1913 after applying our filtering process). We provided an overall summary of the dataset and how it can be analysed to generate gamified strategies that can be used in educational environments. This dataset can contribute to different fields regarding the use of tailored gamification in education. It contributes to the field of gamification design by using AI algorithms to generate new strategies, it also contributes to the field of personalised and adaptive learning, since the strategies can be tailored to learners' demographics (age, gender, and country), especially supporting gamification and instructional designers, as well as used in research regarding gamification design in educational contexts.

Regarding the limitations of our work, since this dataset is based on a survey, the same limitations of studies of this type apply, including potential subjectivity of questions, and issues with the way the survey was built or presented to the respondents. To mitigate these issues, we opted to use the instrument presented in [Toda et al. 2019], since it was validated by experts in the field of gamification in education. Concerning the presentation of the questions, we used a randomising function present in the tool (i.e., Google Forms) so the order of the questions was not the same for all of the respondents. We opted to apply the survey online, so they could answer it at their own time and pace, minimising issues related to the respondent's mental state at the time.

Another limitation is the preponderance of North American respondents, which might influence future analyses. In addition, the fact that we did not collect the educational level of our respondents is a potential weakness of the dataset. However, it is reasonable to expect that people having access to the Internet and playing games have some minimal level of education, and managed to form expectations about it. Another important aspect is that the survey was designed in English for global usage, which means that Brazilian (and also other countries) responses where obtained from learners with a basic degree of English language.

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