



ECO CITY APP

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Project Report of E-Health Methods and Applications (054301, 10 CFU)

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1. Introduction

Climate change stands as one of the most pressing and relevant challenges of our time, underscoring its urgency through its worldwide repercussions. Despite overwhelming scientific evidence connecting it to human activities, especially greenhouse gas emissions, skepticism and ongoing debate persist [1].

The main objective is to develop an interactive game using Unity 3D, offering players an engaging and highly personalized learning experience. The fundamental purpose is to educate players about the impact of their everyday actions on climate change and the environment, motivating them to reflect on their choices within the game and in real life, and to adopt more sustainable and responsible practices.

By incorporating challenges and decision-making scenarios into the game, players will develop a deeper understanding of the impact of their daily actions on the environment. Through a highly personalized gaming experience, we aim to inspire a more responsible attitude towards the environment and encourage positive actions to address the global challenge of climate change.

2. State of the art

The uncertainties surrounding climate change and skepticism about its causes present significant obstacles to translating climate change knowledge into sustainable behavior change. Therefore, addressing these challenges has gained importance in recent years, as evidenced by the growing interest in climate change education, reflected in the rising number of serious games related to climate change [2].

As a result, current games addressing climate change cover a wide spectrum of topics, including urban development, agriculture, individual actions, water management, climate adaptation, and the attribution of climate risks. These games come in various technical features and formats. Despite the growing popularity of online games, roleplay and management games remain the prevalent designs [3].

The evolving panorama of serious games reflects the need to communicate the urgency of climate action through different strategies and bridge gaps in public understanding. Through the development of our own serious game on climate change, we aim to employ interactive storytelling, simulation, and immersive experiences to confront and address skepticism, offering players tangible examples of environmental impacts.

3. Data Cleaning and Exploratory Data Analysis

This study is based on information obtained from the responses of 160 individuals to a series of predefined questions.

3.1 Data Cleaning

In this phase, a series of operations were executed to prepare the raw data for the analysis. This step was crucial to ensure the reliability, consistency, and appropriateness of the data. The key steps in this process included:

- Handling missing data

Missing data was identified and managed. In particular, missing data in the 'age' and 'education' columns in our dataset were addressed, by filling them with the mean value of respective the columns. This operation allowed us to preserve the maximum number of samples.

- Feature Selection

We conducted feature selection to highlight pertinent columns with our analysis objectives. In this context, we preserved several columns, including 'age,' 'education,' 'heas_1' to 'heas_13,'

and 'ccs_1' to 'ccs_12.' However, the columns 'Gender,' 'marital,' and 'income' were omitted from the analysis due to subsequent findings regarding the performance of the Clustering algorithm and the results of the statistical analysis.

- Reverse scoring of variables

Certain variables needed a transformation to conform to the desired metrics. We utilized the "reverse score" technique on specific columns, including 'ccs_3,' 'ccs_6,' 'ccs_7,' 'ccs_12,' and 'heas_1' to 'heas_13,' to obtain inverted scores. This adjustment was implemented to standardize the scales of the variables.

- Creation of new features

In this phase, we followed the data preparation protocol outlined by De Graaf Janna A. et al. (2023) as a guiding framework. This approach involves evaluating Climate Change Skepticism by reducing the 12 measured items into four dimensions: 'Attribution Skepticism', 'Impact Skepticism', 'Trend Skepticism' and 'Response Skepticism' This was achieved by computing the mean value of three original columns related to CCS for each new column. A similar process was applied to the features associated with the Hogg Eco-Anxiety Scale [4].

- Scaling

Data were scaled using two different scalers: min-max scaler and standard scaler. This scaling was carried out to facilitate the application of clustering algorithms and determine the most optimal outcomes.

3.2 Exploratory Data Analysis

Conducting Exploratory Data Analysis (EDA) allowed us to gain a thorough understanding of the numerical data distribution within the dataset, aiding in the identification of patterns and insights. The histograms of *Figure 1* vividly illustrate the frequency of values across different features, contributing to an enhanced comprehension of the dataset.

In the EDA process, we specifically focused on non-Boolean attributes. The initial step involved univariate analysis, with the histograms of Eco-Anxiety features being particularly noteworthy. Contrary to expectations, these histograms revealed a left-skewed distribution. The elevated levels of anxiety regarding Climate Change were not anticipated by any of our group members.

4. Personas Creation

In this section, we detail the analysis conducted on the data to personalize the game and craft Personas. The goal was to extract relevant insights from the existing population data, facilitating the development of user-centered design tools, such as Personas. This involved a three-step process applied to the dataset: Clustering, Statistical Analysis, and the creation of Persona Cards.

4.1 Clustering

In this section, the clustering analysis is documented, where the primary objective was to segment our dataset into distinct groups to reveal patterns and insights within the data. Clustering has been employed to uncover hidden structures and relationships among the data points. The following list outlines the key aspects of our clustering analysis:

- Exploration of multiple clustering algorithms

To determine the most suitable clustering method for our dataset, we explored three different algorithms: Hierarchical Clustering, K-Means, and DBScan. Each algorithm offers unique characteristics and benefits, and our goal was to identify the one that best suited our data and objectives. The algorithms were each tested for both our scaled datasets.

- Evaluation using silhouette score

To assess the quality of the clusters generated by each algorithm, we utilized the silhouette score. The silhouette score provides a measure of the cohesion and separation of the clusters, with higher values indicating better cluster quality. This metric was instrumental in the selection of the final clustering method.

- Selection of hierarchical clustering

After a thorough evaluation, Hierarchical clustering using data scaled through MinMaxScaler emerged as the preferred method for our analysis. The decision was driven by the homogeneity of the clusters and the values of the silhouette. From these metrics, we observed that the optimal number of clusters is three as reported in *Figure 2*.

4.2 Statistical Analysis

Statistical Analysis was conducted to assess significant differences among the identified clusters, using specific tests tailored to the nature of the variables involved.

The variables were divided into two categories: quantitative and categorical variables.

Quantitative Variables: we employed the Kruskal-Wallis test, followed by the Pairwise Mann Whitney U test. The results indicate statistically significant differences among the clusters for quantitative variables. Therefore, we chose to retain these variables in the dataset as they significantly contribute to the observed diversification among the groups.

Categorical Variables: we adopted two distinct approaches based on the presence of values in the contingency table below five.

- Chi-Square Test: applied to variables with all values in the contingency table greater than five.
- Fisher Test: utilized for variables with values below five in the contingency table, implemented with Python for binary features and with R for non-binary ones.

Throughout this phase, the aim was to find a means to justify the creation of the three groups and assess whether each feature provides distinct information within the groups.

We then computed the p-value for each feature by comparing both the three groups together and the groups paired. This last method was used to express the differences in each feature between the groups in *Table 1*.

Based on the results of the tests on categorical variables, we decided to eliminate the 'Gender', 'Marital status', and 'Response Skepticism' features as the statistical analysis highlighted their lack of relevance in cluster diversification.

Comprehensive details of the results are reported in *Table 1*, including the associated p-values obtained from comparisons across all clusters together.

4.3 Persona Cards

The preliminary step preceding the creation of the Persona cards was an Excel table that summarizes the central tendencies of each Persona.

The mode of each feature was considered as a central tendency metric, hence expressing the occurrence of each attribute for the persona groups.

Based on the information retrieved by the Statistical Analysis, we developed the Persona Cards. The pictures used were obtained with an AI-based image generator online, while names were made up randomly. Quantitative information, such as demographic data, personality, goals, etc. was obtained from the data analysis.

5. Game Design

We develop a sandbox-like game, centered around building the most green and sustainable city as possible. To start the game, players are asked to fill in a questionnaire, to associate them with a specific cluster. Based on the assigned cluster, the player begins a personalized gaming experience. As players embark on this virtual journey, they're initially equipped with basic structures to build their city, such as streets and houses. Unlocking new structures requires successfully answering quizzes related to each structure's topic. Once the user answers the quizzes there is a brief description of the topic. This and the

user's opportunity to redo the questions if they answered wrong, encourage learning and underline the dynamic nature of the game.

To build new structures, the player invests Game Money. Starting the building process requires initial spending, while the return on the investment comes from cashing the taxes from the new citizens that automatically populate the new buildings.

A significant structure to be unlocked is the University, since it allows the user to unlock avenues for research, allowing players to make advancements in renewable energy or pollution reduction filters. The progress of this research is visually represented through a completion bar, adding a layer of challenge to the gameplay.

The user loses the game if the amount of Game Money remains negative for more than a minute.

The target audience is players aged 16 and older seeking an interactive learning experience about the environment and climate change.

5.1 Personalization: Tailoring the Experience

One of the unique features of our game lies in its personalization techniques. The climate change indicators associated with in-game structures differ based on the player's cluster. These indicators serve to portray the current state of the game, encompassing both general metrics like crime rates, money, and population, as well as climate-focused metrics such as carbon dioxide production and particle pollution.

It is important to highlight that for those who appear skeptical about climate change, these indices have a higher impact on the game, showing immediate and pronounced consequences of unsustainable actions. Conversely, environmentally conscious players have a game where the indexes are attenuated.

In the game, there are also catastrophic events: acid rain, smog events, and heatwaves. These dynamic events add an extra layer of challenge, emphasizing the intricate relationship between player choices and the health of their virtual city. These catastrophic events are less likely to occur for eco-anxious players by reducing the probability for them to occur.

The overall objective remains consistent: transform the city into an eco-friendly space without succumbing to financial ruin.

Appendix

Table 1: Personas Table

| | Group 1 (n=53) | Group 2 (n=53) | Group 3 (n=54) | P value |
|-------------------------|----------------|----------------|----------------|---------|
| Age | 19 (13.2%) | 42 (11.3%)* | 42 (14.8%)* | <0,001 |
| Education | 18 (34%) | 8 (45.3%)* | 13 (57.4%)*# | <0,001 |
| Income | 33000 (11.3%) | 21000 (9.4%)* | 29000 (11.1%)# | <0,001 |
| Attribution Skepticism | 1 (26.4%) | 3 (34%)* | 2.7 (31.5%)*# | <0,001 |
| Impact Skepticism | 0.3 (26.4%) | 3 (39.6%)* | 0.3 (29.6%)# | <0,001 |
| Trend Skepticism | 1.3 (30.2%) | 3.3 (30.2%)* | 2 (33.3%)*# | <0,001 |
| Response Skepticism | 2.7(26.4%) | 1.7 (30.2%) | 1.7 (27.8%) | 0,938 |
| Affective Symptoms | 0.8 (20.8%) | 3 (43.4%)* | 2 (18.5%)*# | <0,001 |
| Rumination | 0.3 (17%) | 3 (50.9%)* | 2 (29.6%)*# | <0,001 |
| Behavioural Symptoms | 1.7 (18.9%) | 3 (67.9%)* | 2 (31.5%)*# | <0,001 |
| Anxiety Personal Impact | 1 (18.9%) | 3 (60.4%)* | 2 (27.8%)*# | <0,001 |

Figure 1: Histogram of the Features

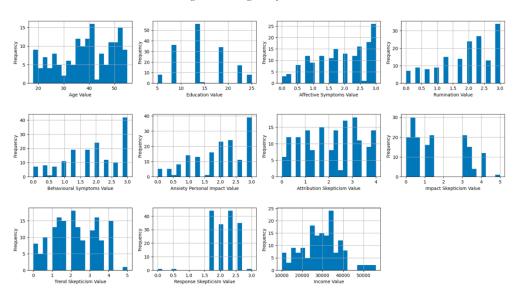
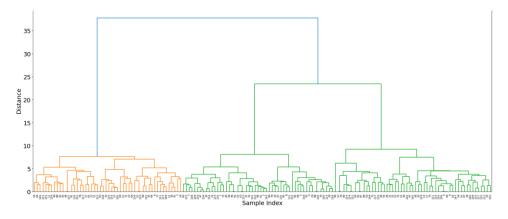


Figure 2: Hierarchical Clustering Dendogram



References

- [1] DE GRAAF, Janna A., et al. The climate change skepticism questionnaire: Validation of a measure to assess doubts regarding climate change. Journal of Environmental Psychology, 2023, 89: 102068.
- [2] Neset, T.-S.; Andersson, L.; Uhrqvist, O.; Navarra, C. Serious Gaming for Climate Adaptation—Assessing the Potential and Challenges of a Digital Serious Game for Urban Climate Adaptation. Sustainability 2020, 12, 1789.
- [3] Reckien, D.; Eisenack, K. Climate Change Gaming on Board and Screen: A Review. Simul. Gaming 2013, 44, 253–271.
- [4] Hogg, T., Stanley, S., O'Brien, L. V., Wilson, M., & Watsford, C. (2021, March 12). The Hogg Eco-Anxiety Scale: Development and Validation of a Multidimensional Scale.