Artificial Intelligence Based Procedural Content Generation in Serious Games for Health: The Case of Childhood Obesity

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Abstract. This paper presents a novel Procedural Content Generation (PCG) method aiming at achieving personalization and adaptation in serious games (SG) for health. The PCG method is based on a genetic algorithm (GA) and provides individualized content in the form of tailored messages and SG missions, taking into consideration data collected from health-related sensors and user interaction with the SG. The PCG method has been integrated into the ENDORSE platform, which harnesses the power of artificial intelligence (AI), m-health and gamification mechanisms, towards implementing a multicomponent (diet, physical activity, educational, behavioral) intervention for the management of childhood obesity. Within the use of the ENDORSE platform, a pre-pilot study has been conducted, involving the recruitment of 20 obese children that interacted with the platform for a period of twelve weeks. The obtained results, provide a preliminary justification of PCG's effectiveness in terms of generating individualized content with sufficient relevance and usefulness. Additionally, a statistically significant correlation has been revealed between the content provided by the proposed PCG technique and lifestyle-related sensing data, highlighting the potential of the PCG's capabilities in identifying and addressing the needs of a specific user.

Keywords: serious game · adaptive · procedural content generation · genetic algorithm · health · sensors · childhood obesity

A. Cunha et al. (Eds.): MobiHealth 2022, LNICST 484, pp. 207–219, 2023.
https://doi.org/10.1007/978-3-031-32029-3_19

1 Introduction

Serious games (SG) are games with a primary purpose other than entertainment and constitute a widely recognized and effective means for educating, raising awareness, and driving behavioral changes [1, 2]. Health interventions based on SGs benefit greatly from the ability to provide a safe virtual environment, enhance engagement [3], and deliver immediate feedback [4, 5]. Furthermore, SGs can potentially tailor game content according to player needs towards personalized health interventions [6]. A recent review study employs the term "individualization" to describe SGs with adaptive capabilities. Individualization can improve user experience and engagement, as well as promote knowledge acquisition. Delivery of individualized content can be achieved either through tailored game design or by algorithmically generating content to match the user's personalized needs [7].

PCG is a method of creating content algorithmically, often based on artificial intelligence (AI) techniques, and is commonly employed to produce a large amount of novel content (i.e., game maps, dungeons, Non-Player Characters - NPC). Two main approaches to PCG exist, one that relies on random generation of content and a second that takes into consideration player interaction data [8]. Data gathered from a variety of sensors can also be integrated into PCG techniques. With the integration of such types of data in the PCG workflow, the content provided is usually relevant to the desired SG target, maximizing user engagement and thus adherence to the intervention.

SGs for health benefit greatly from the incorporation of state-of-the-art sensing technology [9]. PCG techniques employing sensing data can produce patient-tailored and clinically relevant content, resulting in a smart personalized health intervention. More specifically, the availability of real-time sensing data providing information regarding the user's lifestyle, behavioural habits and health status, makes feasible the development of sensor-based adaptive SGs with increased capacity to address important challenges in self-health management [10]. Moreover, current research on PCG in SGs for health highlights the potential of the technology to generate game content automatically and on-demand, thus reducing the time and effort needed for design purposes and increasing replayability [11, 12].

A few publications on SGs for health incorporating PCG techniques that employ sensing technology have been identified in the relevant literature. "The Emotional Labyrinth" tracks physiological signals (e.g. heart rate, electrodermal activity, breathing rate) to assess user emotion and create PCG environments to help the player achieve emotional self-awareness [13]. Another PCG based SG intervention focuses on stimulating motor movement in stroke patients through utilizing basic gesture expressions captured by applying Kinect and Myo [14]. In a recent study, the importance of a PCG-based SG in improving user-experience has been highlighted. Focusing on training individuals with sleep apnea in self-disease management, the SG includes a card game where the player faces procedurally generated opponents. The opponents are created by a PCG method employing a genetic algorithm (GA), taking into consideration the player's performance through their interaction with the SG [15]. GA is a AI-based heuristic approach that falls into the category of evolutionary algorithms.

The present study focuses on the generalization of this PCG methodology towards its integration in the ENDORSE platform [16]. In particular, the method has been enhanced to receive and analyze data from lifestyle and clinically relevant sensors in real-time. Preliminary results from the integration of the proposed methodology in the ENDORSE platform are presented for the case of childhood obesity.

2 Materials and Methods

2.1 The ENDORSE Platform

The ENDORSE project introduces a novel integrated platform to promote self-health management in T1DM and childhood obesity. The target group involves ages within the range of 6 to 14 years. The platform comprises a mobile SG for children, as well as mobile applications for parents and healthcare professionals, enabling remote health monitoring while providing personalized content. The ENDORSE platform leverages data collected from a multitude of sources that include sensors (Fitbit Ace 2 physical activity tracker, Freestyle Libre continuous glucose measurement sensors), IoT devices (Insulclock smart insulin pen), as well as interaction with the SG and the mobile applications. Personalization is achieved through the incorporation of a recommendation system able to deliver individualized content. Content generated by the ENDORSE recommendation system consists of two distinct parts: game missions and messages. The messages are made available to the children through the SG interface and to the parents through the mobile application.

The ENDORSE SG consists of a variety of mini-games in the form of missions of two types: educational and action. Healthcare professionals have been intensively involved in the SG design activities in order to assure the validity and efficiency of the SG's educational and behavioral goals. Through gameplay, the user collects in-game currency and food ingredients. The currency can be spent in avatar customization, whereas food ingredients can be used in a meal preparation mini-game to collect further rewards. In addition, educational and progress messages appear daily in a predefined game space. The messages selected by the ENDORSE recommendation system come from a pool of messages created by the healthcare professionals. Educational messages include tips and advice about healthy lifestyle and disease self-management. Progress messages are motivational and provide positive reinforcement based on the progress monitored by the platform's sensors. Aiming at minimizing the SG's impact on total daily screen time, only two game missions, an educational and an action, are available each day.

In the pre-pilot phase of the ENDORSE platform, four total missions have been included. “Cross the Swords” (Fig. 1a) and “Dive and Rise” (Fig. 1c) are action missions and “Fruit Ninja” (Fig. 1d) and “Balance Beam” (Fig. 1b) are educational missions. In “Dive and Rise” the player is incentivized to collect as many healthy foods as possible while controlling a swimming avatar. “Fruit Ninja” is a mission that requires the player to slice different kinds of food that follow a random parabolic path across the screen. A designated bar fills as the mission progresses. The mission is successful if the sliced food ingredients are considered ideal snack options. “Balance Beam” presents a narrow bridge that the avatar has to cross while maintaining balance by using a paddle. A random food appears on one side of the paddle and the player has to pick its quantity (correct portion). While choosing the right portions the avatar maintains its balance. “Cross the Swords” places the avatar in a reflex contest against a creature. The player has to react quickly and pierce different kinds of snacks. The daily missions are accessible through an in-game map (Fig. 2a).

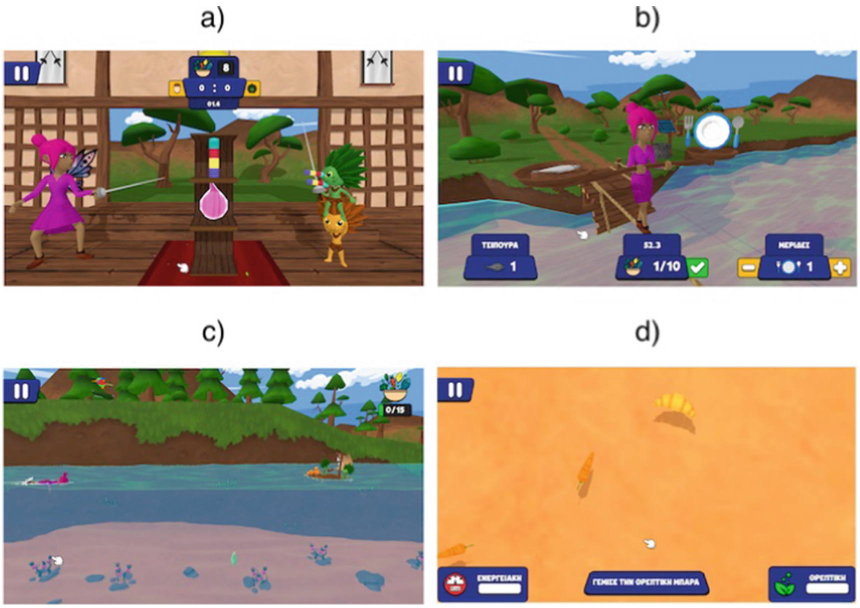

Fig. 1. Gameplay screenshots from game missions. (a) “Cross the Swords” (b) “Balance Beam” (c) “Dive and Rise” (d) “Fruit ninja”

Finally, a meal preparation mini game ("balanced meal" or "lunch box") is always accessible in the game lobby (Fig. 2b). All the ingredients that the player collected in the missions are available there for use. The player places the various food ingredients in the "lunch box" for evaluation. They are rewarded with coins based on their ability to create balanced meals.

The ENDORSE mobile application that is available to the parents serves four purposes. Firstly, it hosts a section that displays the messages delivered by the ENDORSE recommendation system on a daily basis. In addition, it provides a portal, where the parents can communicate with the healthcare professionals in the form of message exchange. It also gives the opportunity to the parents to enter the weekly weight of their children as well as their dietary options on a daily basis. Lastly, the application serves as a means of distributing the required questionnaires to the parents, such as the Post-Intervention Feasibility Study Questionnaire.

Fig. 2. (a) The mission selection screen. On the top right is the notification bell that rings whenever the user has an available message delivered by the ENDORSE recommendation system. (b) The meal preparation screen. On the right, the available ingredients are shown.

2.2 Genetic Algorithm

The proposed PCG technique generates SG content based on a Genetic Algorithm (GA). This technique has been initially incorporated into a card SG aiming to promote self-health management and raise awareness for obstructive sleep apnea through simulated debates against NPCs [15]. The ENDORSE Recommendation System utilizes an extended version of the GA that procedurally generates personalized content, taking into consideration sensor data collected by the ENDORSE platform.

For the integration of the PCG technique in the ENDORSE platform, SG missions and displayed messages have been encoded in binary gene values, with "1" representing content presence. A collection of genes constitutes a chromosome, while each gene is represented by a designated chromosome position. As depicted in Fig. 3, chromosomes have been split into two parts. The first part (MG) includes genes that determine the daily availability of missions for the SG. The second part (RG) is responsible to select tailored messages that will be displayed to the end-users. The GA is initialized with a population of chromosomes, each characterized by a selection of genes that correspond to either the availability of a mission or the display of a particular message. A total of 380 GA's chromosomes are generated for the initial population to provide adequate diversity among the chromosome population. Each gene has a 5% probability to mutate in order to adjust for chromosomes with limited diversity. Furthermore, the length of the chromosomes has been significantly enlarged compared to the original approach [15], containing 103 genes in order to accommodate 28 of them for mission content and 75 for messages. Constraints have been applied to the chromosomes to limit the availability of daily game missions. No chromosome is allowed with more than two missions per day, while each day contains one educational and one action mission. A chromosome is selected randomly as a representative and generates initial content for the ENDORSE platform. Based on data collected from sensors and user interaction, a fitness function (see Eq. 1) is applied to determine the fittest chromosomes from the initial population.

Fig. 3. Chromosome layout. MG refers to Mission Genes, RG to Recommendation Genes

$$FS = W_{MG1} * MG1 + \ldots + W_{MG28} * MG28 + W_{RG1} * RG1 + \ldots + W_{RG75} * RG75 \quad (1)$$

The fitness function employs weights (W_{gene}), assigned to each gene, representing the desirability of the gene's presence in the next GA state. These weights are trained according to the content they control which defines constants a_x and b_x, based on relevant data collected by the ENDORSE platform. Weights for game missions are trained based on SG interaction data as seen in Eq. 2.

$$W_{MG} = \begin{cases} W_{MG} + a_1, \ \textit{if mission score is low} \\ W_{MG} - a_2, \ \text{if mission score is high} \\ W_{MG} - a_3, \ \text{if mission is played} \end{cases} \quad (2)$$

Weights controlling the display of messages are trained based on multimodal data collected from the platform's sensors. Specific thresholds have been applied on the obtained sensing data towards classifying every day as good, medium, or bad, in terms of recognition of healthy lifestyle habits and self-health management. For educational messages, Eq. 3 is applied.

$$W_{RG} = \begin{cases} W_{RG} - b_1, \ \text{for each good day} \\ W_{RG} - b_2, \ \text{for each medium day} \\ W_{RG} + b_3, \ \text{for each bad day} \end{cases} \quad (3)$$

For progress messages the weight training follows Eq. 4.

$$W_{RG} = \begin{cases} W_{RG} + b_1, \ \text{for each good day} \\ W_{RG} - b_2, \ \text{for each medium day} \\ W_{RG} + b_3, \ \text{for each bad day} \end{cases} \quad (4)$$

This weight training ensures that the GA promotes content that is linked to identified player needs, replicating it further and passing it on to new generations. SG missions where the player scores poorly are promoted over missions that are either played frequently or are completed with high game scores. Educational messages linked to healthy behaviors monitored by the platform's sensors have a lower chance of appearing. Progress messages are more likely to appear to progress healthy habits or remind about identified unhealthy tendencies.

At the end of each GA iteration, the fittest chromosomes are paired to produce the new generation. The 20 highest scoring chromosomes are selected, based on the score provided by the fitness function, to create a next generation of chromosomes that has the same population as the original, through the crossover. One of those is also chosen to be the representative, responsible for providing the system's content.

Crossover (see Fig. 4) occurs separately for the mission content and the messages (MGs and RGs) to ensure the structural integrity of the offspring and its compliance with the constraints. For each pair of chromosomes, the MGs and RGs are split independently (Fig. 4a) into two segments at a random point (i.e., MGA1 -MGA2, RGA1 – RGA2 for

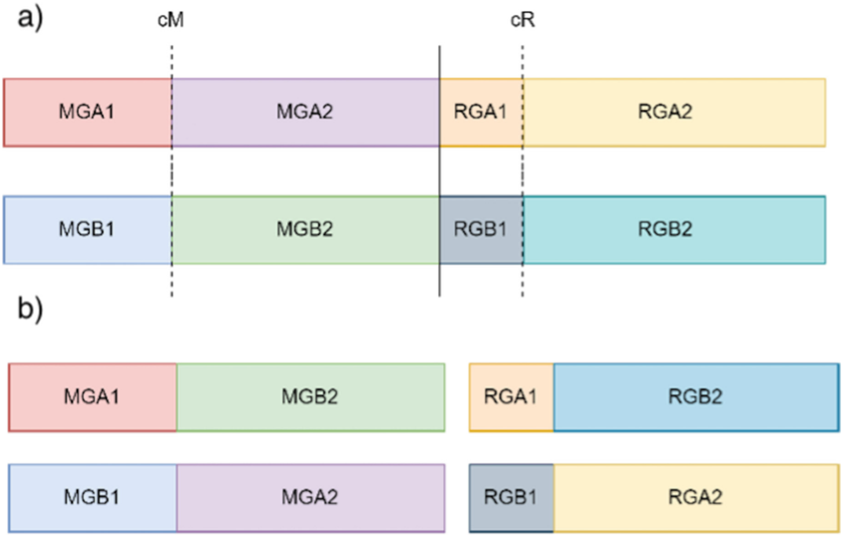

Fig. 4. Chromosome crossover. (a) Two random markers, cM and cR, split the chromosomes. (b) Two new gene sequences for MG and two for RG are generated. Their combinations produce four offspring.

chromosome A). Then each segment of the chromosomes is combined with another to create two sets of new MGs and RGs (Fig. 4b). Finally, the MGs and RGs are combined in four ways resulting in four total offspring.

Algorithm 1 presents a summary of the process of updating the GA for a new generation. The algorithm accepts as input a collection of data from the previous GA state for each user as well as data from their interaction with the platform and data gathered by the activity tracker. Its output is the generation's representative chromosome. As described, the crossover happens separately for MG and RG (lines 6 and 15) and takes into account the previous generation's fittest chromosomes. In case the newly selected representative RG or MG is exactly the same as the previous generation's one, the chromosome population is deemed saturated and is reinitialized while keeping the same weights (lines 9–11 and 18–20). Then the representative is redrawn out of the newly created fittest chromosomes. This process acts as a way of adding genetic diversity to the population, in case the gene mutation isn't enough. Lastly, the function saves the current GA state that will be retrieved in the following iteration's update.

Algorithm 1: Genetic Algorithm Update

```
Data:     Previously selected chromosome CH
          Previous generation Gen, its difficulty D and its weights W, user
          interaction with the platform UI and data from activity tracker UD
Result:   Newly selected chromosome CH

function NewGeneration(CH, Gen, D, W, UI, UD)
   previous MG, previous RG ← split CH
   # region Serious Game
   D ← CalculateNewDifficultyMG(MG, D, UI)
   W ← CalculateNewWeightsMG(MG, W, UI, UD)
   Gen ← CrossoverMG(Gen, W)
   Gen ← MutationsMG(Gen)
   new MG ← SelectChromosomeMG(Gen, W)
   if new MG same as previous MG
      Gen ← InitialisePopulationMG(W)
      new MG ← SelectChromosomeMG(Gen, W)
  # endregion
  # region Messages
   W ← CalculateNewWeightsRG(RG, W, UI, UD)
   Gen ← CrossoverRG(Gen, W)
   Gen ← MutationsRG(Gen)
   new RG ← SelectChromosomeRG(Gen, W)
   if new RG same as previous RG
      Gen ← InitialisePopulationRG(W)
      new RG ← SelectChromosomeRG(Gen, W)
   new RG ← ApplyRGMask(new RG)
   # endregion
   CH ← concatenate new MG and RG
   CreateNewSave(CH, Gen, D, W)
   return CH
```

2.3 Validation Framework

The PCG technique as part of the ENDORSE recommendation system was validated in terms of user acceptance, and accuracy of the delivered personalized content during the ENDORSE pre-pilot obesity study. Twenty (20) obese children (aged 6–14) participated in the pre-pilot study for 12 weeks. The ENDORSE game and a Fitbit Activity Tracker [17] were used by the participating children, while the ENDORSE mobile application was used by their parents. The ENDORSE pilot trial has been approved by the national and ethical committee.

The intervention included 12 iterations, each lasting one week. During each iteration, data regarding the children's physical activity were gathered and fed into the GA's fitness functions. Simultaneously, data accounting for the children's interaction with the content and missions of the SG were collected. One of the GA's highest-scoring chromosomes was designated representative and was responsible for providing the weekly content.

The report produced by the Fitbit activity tracker included the daily number of steps, sedentary time and sleep time. For each participant, the average steps per day were calculated excluding those days with less than 2000 steps. This cutoff was set as an indicator of applying the Fitbit Activity Tracker. Similarly, the average sleep duration was measured, taking into consideration those days with greater than 0 recorded minutes of sleep. The thresholds for classifying the days as good, medium or bad were decided according to relevant literature [18, 19].

The integration of the PCG technique was evaluated in two directions. Within the first direction, a post-intervention questionnaire was drafted including questions relevant to the acceptance (Q1, Q2) and usefulness (Q3) of the tailored content [16]. The parents could answer each question with an integer score ranging from 1 to 5. The questionnaires were filled by the parents following the completion of the intervention plan. In the second direction, Pearson's Correlation test was performed on the data gathered from the activity trackers and the messages provided by the GA in order to assess PCG's ability to provide content relevant to the child's lifestyle status. Messages controlled by the GA were split into the following categories: "Physical Activity", "Sedentary Time" and "Sleep Duration". "Physical Activity" and "Sedentary Time" were correlated with average daily steps per participant and "Sleep Duration" with average sleep duration. Each of these categories was represented in the GA by two genes, one designated for educational messages and the other for progress messages. Pearson's correlation was calculated for these genes both separately and in combination, with the relevant data collected from sensors.

3 Results

The scores obtained from questions relevant to the acceptance of individualized content are presented in Table 1. Overall, a positive score was awarded to all three questions. The highest score was achieved in Q2, investigating the usefulness of the displayed messages towards the achievement of their personal goals (Q2: 4.13 points). The weakest score was reported in Q1, regarding the relevance of the displayed messages to the child's needs, (Q1: 3.07 points). A statistically significant difference (1.04 points, $p = 0.0217$) was identified by applying the Student's t-test between questions Q1 and Q2, regarding the relevance and the usefulness of the messages displayed through the SG.

Table 1. Post-Intervention Questionnaire

Questions	Scores	
	Mean Value	Standard Deviation
Q1: How relevant to your child's needs did you find the messages shown through the game?	3.07	1.38
Q2: How useful did you find the daily messages you received to achieve your goals?	4.13	1.06
Q3: How useful did you find the game's ability to display educational messages?	3.40	1.50

Pearson's correlation results are presented in Table 2. Among all participants, the average steps per day were 9840.6 and the average sleep duration was 458.6 min. Out of the 20 participants, 2 were dropouts and 3 didn't respond to the post-intervention questionnaires. Negative correlations were observed in all the investigated combinations. Statistical significance was revealed between the number of "Physical Activity" messages sent to the average steps ($p = 0.042$) and the number of combined "Physical Activity" and "Sedentary Time" messages to the average steps ($p = 0.030$).

Table 2. Pearson's Correlation

Category	Correlation		
	Gene 1	Gene 2	Combination
Physical Activity	−0.20	−0.30	**−0.45**
Sedentary Time	−0.17	−0.25	−0.29
Physical Activity and Sedentary Time	-	-	**−0.48**
Sleep Duration	−0.23	−0.11	−0.19

4 Discussion

Answers to the post-intervention questionnaires indicate overall acceptance regarding the individualized content provided by the GA. However, a statistically significant difference was found between message relevance and usefulness. Based on the answers to Q1 and Q2, the messages sent by the GA were regarded by the participants as more useful than relevant. This may rely on the fact that the messages were designed by healthcare professionals specifically for the SG intervention and thus inherited general usefulness to the health condition of the recipients. On the other hand, the message's inclusion in the SG content was defined by the GA. Despite its ability to recognize and promote relevant messages, a comparatively lower score on Q1 is to be expected, as one of the

GA's primary directives is the diversification of content. Both scores, though, indicate that the messages had a positive effect in the SG setting.

The negative correlations presented in Table 2 show GA's sensitivity to trends regarding lifestyle and self-health management habits captured by the platform's sensors. When users displayed high levels of physical activity, the frequency of related messages declined and vice versa. The fact that this same pattern was observed in every category, in some cases even with statistical significance, shows the general success of GA's functionality. The fitness functions managed to translate user trends into appropriate changes in gene weights, thus enabling the GA to perform the natural selection of the most suitable genes for its chromosomes. Furthermore, the GA avoided reaching very high values of negative correlations, which would be a sign of content saturation. The non-deterministic selection of content performed by the GA provided the ENDORSE recommendation system with the capability to occasionally omit certain categories with high weights in favor of others with lower. Such behavior highlights the difference between a rule-based system and the GA, in terms of providing varying personalized content.

Results from this preliminary analysis were collected within the pre-pilot phase of the ENDORSE project. The ENDORSE pilot studies, which feature a SG version with additional game missions and enhanced functionalities in the ENDORSE recommendation system, have been recently concluded. Analysis of the newly acquired data is expected to provide further insight regarding the GA's capabilities to produce individualized content.

5 Conclusion

In this study, we presented the integration of a novel GA-based PCG approach into the ENDORSE platform which harnesses the power of Artificial Intelligence, m-health and gamification mechanisms, towards implementing a multi-component intervention for the management of childhood obesity. The PCG approach automatically provides the platform with SG content and educational messages by collecting data from physical activity sensors and interaction with the SG. Post-intervention analysis revealed the potential of the proposed PCG methodology to adapt to user data and provide relevant content. The impact of the individualized content on the users will be analyzed in a future study.

Acknowledgments. This research was supported within the framework of the ENDORSE project, which is funded by the NSRF. Grant agreement: T1EΔK-03695.

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