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# Learning prosocial skills through multiadaptive games: a case study

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**Abstract** Digital games introduce an innovative means for teaching prosocial skills to students; however, the lack of proper personalization features in the games may result in the degradation of the learning process. This paper aims to study whether the performance of students in a prosocial game could be improved by an intelligent AI adaptation mechanism. To this end, a novel hybrid adaptation manager capable of assisting students playing prosocial games is presented. Our approach consists of a combination of two adaptation mechanisms that process personalization information both offline and in real-time. Both implementations are based on artificial intelligence techniques and adjust game content in order to increase the chances of players attaining the game's specific learning objectives concerning prosocial skills. In particular, the online mechanism maintains a player engagement profile for game elements that are intended to represent the pedagogical practices of corrective feedback and positive reinforcement. On the other hand, offline adaptation matches players to game scenarios according to the players' ability and the game scenarios' ranking. The efficiency of the proposed adaptation manager as a tool for enhancing students' performance in a prosocial game is demonstrated through a small-scale

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experiment, under real-time conditions in a school environment, using the prosocial game "Path of Trust."

**Keywords** Game adaptation · Prosocial skills · Engagement · Serious games

## Introduction

At the apex of the information era, a wide range of innovative technologies has been established for the delivery of educational content. These technologies incorporate features and conveniences that make them more attractive to the learner than traditional education methods. A prominent example of such a technology that has met the increasing interest of research communities in recent years is digital educational games (DEGs). More specifically, DEGs target the education sector and have the potential of administering educational knowledge within an interactive, engaging, and immersive experience (Law et al. 2008; Kickmeier et al. 2011). In fact, game-based learning (GBL) has been the subject of several research studies recently (Cheng and Su 2012; Wouters and Oostendorp 2013; Plass et al. 2015). In order to realize knowledge development, GBL requires the definition of specific learning objectives that the player has to achieve in order to complete the game. Weitze et al. discuss the distinction between learning objectives and game goals, explaining that the former consist of the knowledge or abilities that we want the player to learn, while the latter correspond to in-game tasks mandatory for completing the game (Weitze 2014). This implies that in some games, a learning objective is not the actual game goal, but a means to achieve it.

An innovative type of games that targets the player's social behavior is prosocial games (Gentile et al. 2009). The application of sociological theories to educational technology is not something new, e.g., Bourdieu's theory of practice is an example of a sociological theory that can be adopted in educational technology research to move toward understanding the wider complexities of technology practice (Beckman et al. 2018). Prosocial games have emerged from the need to induce prosocial behavior to children playing video games. Prosocial behavior is defined as the ability of a person to act in ways that benefit others. There have been many efforts by researchers in psychology to provide a more formal definition of prosociality. In particular, Keltner et al. define the SAVE framework which divides prosociality into certain domains, such as, trust, cooperation, altruism, compassion, and empathy (Keltner et al. 2014). A prosocial game then can be designed so that it can model one or more of these concepts by defining a player's learning objective as the expression of the corresponding prosocial behavior.

Although psychology research can help prosocial games define learning objectives for their players, each of the individual objectives may seem hard to complete. Moreover, the induction of prosocial skills within a game requires multiple aspects of a player's behavior to be taken into consideration. In such cases, the addition of personalization capabilities may prove to be valuable and assist the player to complete the game. Besides, it has been argued in multiple studies that serious games need to avoid the one-size-fits-all game design principle and provide personalization features to better suit the preferences of their players (Li and Riedl 2010; Kickmeier et al. 2011; Hamari et al. 2016). In order to satisfy these requirements for player-centric design, game adaptation mechanisms have started to be considered as an essential component of modern serious games. The algorithms behind these technologies have their roots in artificial intelligence research and their central assumption is that adapting game content to certain aspects of player characteristics can assist in learning specific types of skills.

This context brings up the question whether a prosocial game could benefit from the advances in adaptive technologies and include hybrid personalization capabilities that can properly tailor the game to the player's personality. If that could be accomplished effectively, the task of reaching the game's prosocial objectives would be simplified for players.

In this work, we propose an adaptation manager that fulfills this goal and provides enhanced personalization capabilities for prosocial games. In order to test our method, we applied the adaptation manager to a prototype prosocial game and created adaptive content able to assist the player in achieving the game's objectives. The contributions of this work are fourfold: First, we developed two adaptation mechanisms, offline and online mechanisms, which are able to capture and process different types of player characteristics, as well as, adjust different types of content in the game. The offline mechanism concerns the enhancement of the player's in-game ability, while the online is focused on maintaining the engagement state of the player. Second, we created a set of adaptive scenarios that realize learning objectives concerning the expression of prosocial behavior. Third, we have included the pedagogical practices of positive reinforcement and corrective feedback as a means of player guidance during gameplay. We represented those practices as dynamic game elements that are driven by our real-time adaptation mechanism. Finally, we conducted an experiment with the participation of elementary school students, in order to evaluate the efficacy of our proposed method. We have to note here that in our study we consider that the prosocial goal of a game is defined by the game designer/developer and we are assuming that prosocial skills are actually measured by the game. Starting from this point, in this paper we present a generic adaptation framework that can be applied to different prosocial games to help children enhance their performance in the game. The study of different techniques for measuring prosocial skills is out of the scope of this paper.

The remainder of this document is organized as follows. The second section includes previous work done in the areas of game adaptation, and gamification and prosocial skills. In the third section, we introduce the proposed approach for adaptation in prosocial games and provide implementation details about our adaptation manager. Section four, presents the prosocial game that we used as testbed for applying our method. Section five, describes the adaptive content that we created for driving game adaptation. In the sixth section, we demonstrate the experiments and outline the results of our study. Finally, in section seven, the conclusions of this work are discussed.

## Related work

Game adaptation consists of automatic personalization features that are utilized within games and specifically targeted to satisfy the preferences of the players. In its most usual form, adaptation is used to adjust the difficulty levels of a game (Hunicke 2005). Within the context of serious games, developers follow a player-centric approach for designing adaptation mechanisms that assist the players to achieve the game's goals. In particular, Charles et al. outline current approaches to player-centric game design and propose a method which clusters player profiles and adapts the game to each of the categories, accordingly (Charles et al. 2005). A treatise on adaptivity in serious games is given in (Streicher and Smeddinck 2016) in which the authors analyze the approaches to implement adaptation mechanisms, describe the concept of adaptive cycle, and give instructions on when and how to use adaptivity.

In another study, Law at al. address three main challenges for DEGs: adaptive educational technologies to shape learning experience, reduction of the development costs (i.e., reusability of learning resources), and robust evaluation methodologies (Law et al. 2008). They argue that it is critical not to destroy the immersion and gaming experience with intervening knowledge assessments and thus, they propose an approach based on micro and macro adaptivity. Following this direction, the EU projects, 80 days and ELECTRA, realize game adaptation in a twofold manner, targeting a learner's competence as well as motivational state (Steiner et al. 2009; Kickmeier et al. 2011). Likewise, Yang et al. trained an adaptation mechanism on multi-dimensional player styles (Yang et al. 2013). The effects of a fixed pedagogical agent and multi-pedagogical agents are compared in (Diner and Doganay 2017). Their study seeks to investigate both learners' agent preferences and the effects of pedagogical agents on learners' academic success, motivation and cognitive load. In general, for the adaptation of educational games there are two main approaches to produce adaptive content: the offline and online adaptation. The offline adaptation considers a player's profile and is realised in the loading phase of the game, i.e., before the student starts playing. On the other hand, online adaption adjusts game content in real-time based on data collected during gameplay (Van Oostendorp et al. 2013).

Many efforts have been made to base game adaptation on the players' emotional or affective state. More specifically, Chanel et al. used physiological signals to infer the user's emotion during a game and then adapted the difficulty of the game in order to retain the engagement level of the player (Chanel et al. 2011). In another study, Yannakakis and Hallam used a technique called "preference learning" which is based on training an Artificial Neural Network (ANN) to model a player's entertainment level within a game and infer the necessary game adjustments to increase that value (Yannakakis and Hallam 2009). Gilleade et al. focus on affective feedback and used it to influence game play (Gilleade et al. 2005). Furthermore, they proposed a framework for developing affective games, named "assist me, challenge me, emote me." Bontchev (2016) studies emotional adaptation in games by examining studies that used self-reports, observational methods and psychophysiological measurements of both autonomic and central nervous systems (Bontchev 2016). Also, in (Bontchev and Vassileva 2017), affective player metrics have been used for implicit recognition of playing styles that are intended to be further used for style-based adaptation of educational maze games. More recently, Lavoué et al. used matrix factorization for adapting a player typology scheme to gaming features in order to enhance player engagement in a gamified learning environment (Lavoué et al. 2018).

Recently, engagement recognition has been the subject of increasing attention in the fast growing research area of serious games. The work of Newmann first discusses the importance of engagement in the educational process (Newmann 1992). The latter describes student engagement as the student's psychological investment in learning, grasping, or mastering the knowledge, skills, and crafts, not simply a commitment to complete assigned tasks or to acquire symbols of high performance (e.g., grades, social approval). Engagement can be used as a construct to describe an inner quality of concentration and effort to learn. For measuring engagement, Fredricks et al. proposed one of the most frequently cited models of student engagement that is based on three distinct components: affective, behavioral, and cognitive engagement (Fredricks et al. 2004).

Different measurement methods have been explored to capture the complex nature of engagement. The most popular yet time-consuming methods measure engagement using specialized psychometric tests in the form of self-reports (Appleton et al. 2006; Lalmas et al. 2014) or observational checklists (Ocumpaugh et al. 2012). On the other hand, automatic measurement approaches collect engagement data in real-time, thus guiding the learning process by adapting content, as well as, the learning environment toward a more personalized learning. However, such approaches fail to capture the different components of engagement. In order to efficiently measure the student's engagement during gameplay, the multimodal engagement method proposed by Psaltis et al. has been utilized. The latter, combines engagement cues from both the students and the game and can be easily applied to serious game applications (Psaltis et al. 2018).

Another important point to address about game adaptation is the relation between challenge and learning. More specifically, Nogueira et al. argue that the most significant factor for the achievement of immersion in video games is accomplished by keeping a balance between challenges and skills (Nogueira et al. 2013). Hamari et al. correlate the effect of engagement on learning in GBL environments. They conclude that there is virtually nothing as engaging as the state of working at the very limits of your ability. In fact, they argue, the goals should be challenging but achievable, letting the player feel that he will be able to reach the goals, so he does not give up (Hamari et al. 2016).

The importance of adaptive game scenarios has also been well addressed in literature. Qin et al. examined the effects that different scenarios of game difficulty have on player immersion, and concluded that immersion is not proportional to an increasing game difficulty (Qin et al. 2010). Li and Riedl proposed an offline algorithm for adapting human-authored game plotlines (i.e., plotline adaptation) (Li and Riedl 2010). Lopes and Bidarra survey adaptivity in games and conclude that integrating game worlds to game scenarios is the optimal way to implement game adaptation (Lopes and Bidarra 2011). More recently, Kawatsu et al. used the Trueskill rating system (which is an extension to the classic Elo rating system (Elo 1978)) to predict students' decisions in graph-based training scenarios (Kawatsu et al. 2018).

Another subject of study in modern DEGs is whether instructions are effective in the learning process. Weitze gives directions on how to develop the learning objectives of a game, i.e., how to map learning objectives to game mechanics (Weitze 2014). Erhel and Jamet examined the relation between learning instructions and entertainment instructions in GBL. Through their experiment they concluded that the learning instructions elicited deeper learning than the entertainment instructions without impacting negatively on motivation (Erhel and Jamet 2013).

Toward this direction, a theoretical model for teaching and learning social and emotional skills in games was presented in (Star et al. 2016). The model, which is depicted in Fig. 1, consists of five sequential steps:

- *Instruct* verbal and written description of skill and steps to perform the behavior.
- *Model* the behavior or skill is demonstrated step by step.
- *Role-play* imitate or role-play the modeled behavior and skill steps.
- *Feedback* provide in-game performance rewards.
- *Generalize* players identify where and when to use the skill and how to apply it in a variety of circumstances.

In this paper, a game adaptation scheme is developed that blends many of the techniques outlined above and aims to enhance player performance in prosocial games. The proposed adaptation manager follows a simplified version of the theoretical model of Fig. 1 that excludes the Instruct and Generalize steps, and provides an online and an offline adaptation mechanism realizing multi-pedagogical agents that jointly lead the player to achieve the game's learning objective. For the offline adaptation, the mechanism utilizes a modified version of the Elo rating system in order to model the players' ability to accomplish the prosocial learning objectives (PLOs). Within this context, game scenarios are adapted to players in order to provide the proper balance between challenge and skill. For the online adaptation, another online learning algorithm is proposed that learns the player's engagement profile using affective and in-game data. In this case, the mechanism adapts engagement preferences to dynamic game elements that model the pedagogical practices of positive reinforcement and corrective feedback. The experimental results presented in "A testbed for prosocial skills: "Path of Trust"" show that the proposed multiadaptive scheme contributes significantly to the enhancement of the players' performance in the game.


**Fig. 1** Theoretical framework for teaching and learning social and emotional skills (Star et al. 2016)

## The adaptation manager

The purpose of the adaptation manager (PAM) is to provide personalization capabilities to the game and enhance the prosocial behavior of the players. The PAM is divided into two parts, namely the offline and online adaptation mechanisms. The distinction concerns whether the processing takes place during gameplay or before, in the loading phase of the game. These two mechanisms aim to personalize the prosocial games toward maximizing the players' engagement during gameplay, or select appropriate settings (i.e., scenarios) for demonstrating prosocial skills acquisition. The reason for having two distinct mechanisms is to provide our game with better personalization capabilities. Each mechanism processes different information about the player and concerns different types of factors affecting engagement and prosocial behavior.

More specifically, offline adaptation is based on persistent player information that concerns their prosocial skills performance. It aims to match players to the proper game scenario to provide the most appropriate challenge settings (defined by the game's developers) for carrying out the appropriate prosocial skills to succeed. On the other hand, online adaptation considers real-time player data concerning player's engagement estimation through multimodal sensor data fusion sent at specific time intervals during the game. We extract various features related to student's facial expression and body motion in order to estimate his/her affective state and then we combine this information with gameplay features associated with the behavioral and cognitive engagement of the player. This mode of adaptation aims at matching players to the most appropriate game elements which tailor the game to their preferences in a way that aims to maximize their engagement. In the paragraphs that follow, more detailed information about the two mechanisms is provided.

### Offline adaptation

Offline adaptation is realized in the loading phase of the game, as shown in Fig. 2. Its purpose is to select game conditions that are expected to drive the player toward expressing the desired prosocial behavior. These conditions are referred to as game scenarios, i.e., Path of Trust contains a pool of game scenarios offered for offline adaptation. At the start of the game, the adaptation manager checks if stored data concerning the active player and the game exist (i.e., whether the player has already played a session of the particular game before). If data exist, then the game loads the information and fills-in the data structures needed for both offline and online adaptation mechanisms. In cases where there is no existing data, the data structures for the specific player are created and maintained for future use. The offline adaptation executes an ability ranking system and the player is matched with a scenario based on his or hers prosocial ability level. This scenario is then used to initialize the game.

The developed ability ranking system is based on the well-known Elo rating system, which was initially proposed by Arpad Elo (1978). Commonly used for ranking players in chess competitions, the Elo rating system initializes all players

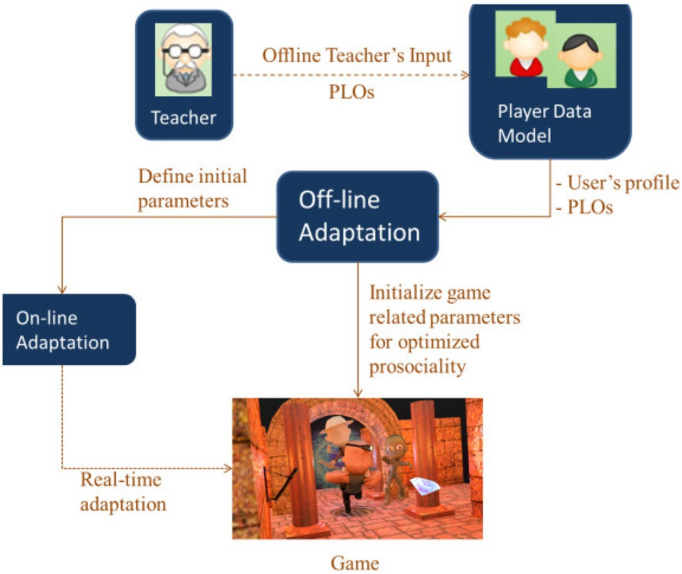



**Fig. 2** Architecture of the offline adaptation mechanism

with the same ranking and, after each game finishes, updates the rankings of the pair of contestants through a set of coupled equations that combine the result of the current game with their previous rankings, using pairwise comparison. More specifically, in order to update the players' rankings, the system compares for each player the actual score that he/she achieved in the game (i.e., quantified value of the chess game result) with a predicted score that is estimated as a function comparing the two players previous rankings. Also, for arranging a chess game, a matchmaking mechanism is used to match players of the same ranking so that each game is fair and challenging. In our case, we attempt to match game scenarios to players according to their competence, hence, the Elo computation is based on pairwise comparisons between players and scenarios. Before each game begins, the offline adaptation mechanism determines the proper scenario for the player, namely, the one that preserves those conditions that maximize his or hers prosocial ability.

We have to note here that our goal was to allow the system to measure automatically and without any external bias (i.e., other kind of measurement) the ability of each player in a prosocial game (and not in the real world). For this reason, we decided to initialize all players with the same prosocial ability level and let the system to estimate their ability rating by itself after each game session. This is also the case for the scenarios i.e., we initially assigned the same rating to all scenarios and let the system free to decide which of them is more challenging based on the game outcomes.

## Online adaptation

Online adaptation is realized during the actual gameplay of the game, as shown in Fig. 3. Its purpose is to select the proper game elements that contribute to the enhancement of the player's engagement in pursuing a prosocial objective, for example, cooperation or trust. These game elements concern the standard pedagogical practices of positive reinforcement and corrective feedback on a student's performance:

- Positive reinforcement is the process of strengthening a person's behavior as a consequence of applying a stimulus.
- Corrective feedback provides instructions to players to correct their behavior and supports them in identifying and paying more attention to the outcome of their actions and what they ought to do to be more successful. It provides specific, often textually represented, instructions to players to correct their behavior and supports them in identifying and paying more attention to the outcome of their actions and what they ought to do to be more successful.

For the online adaptation to be utilized, the game should offer a pool of elements (e.g., text messages, sounds, or graphics) realizing positive reinforcement and/or corrective feedback. These elements compose the user's engagement profile, with all elements having the same buffer size and holding previous engagement estimates ordered in time. The engagement estimations are given by the engagement recognition process (see next sub-section). We chose a small buffer size, holding only the last 5 engagement estimates for every element to build the player's engagement profile.

In order to learn the engagement profile of a player, we used a variation of the $\epsilon$ -greedy algorithm called "$\epsilon$-decreasing," that is commonly used in online machine learning applications (Takahashi et al. 2009). More specifically, this algorithm

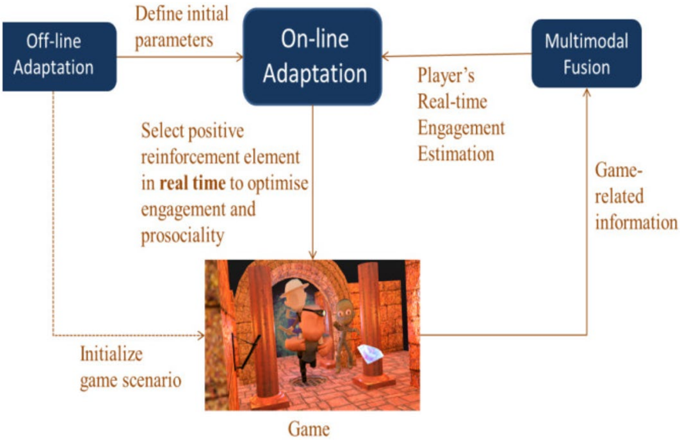



**Fig. 3** Architecture of the online adaptation mechanism

balances exploitation with exploration in a way that gradually favors exploitation over time. Instead of using time as a criterion for exploitation, we defined our criterion to be the user's profile coverage which we estimate through a heuristic function counting nonzero profile values. When the user's engagement profile is filled with values (i.e., coverage is high), the algorithm exploits the profile, and the element that appears in the game is the one that maximizes the player's engagement. We estimate the player's preference for engagement using a weight decay scheme that decreases the importance of engagement estimates through time. On the other hand, if profile coverage is low, exploration is favored over exploitation and the online adaptation recommends a random element to the game.

A player's engagement profile concerns the real-time estimation of the player's engagement state during specific time intervals in the game. The player's engagement estimation is vital within the context of prosocial skills due to the concept's gamification as in-game tasks for building up a set of predefined abilities. For that reason, we devote the following sub-section to the analysis of the engagement recognition process that we followed.

### Engagement recognition

For measuring the affective engagement (affective engagement relates to emotional responses of players to game content), an extension to the facial expression and body motion recognition described in (Kaza et al. 2016) and (Psaltis et al. 2016) has been adopted, which identifies the affective state of the player in the Valance-Arousal space using Microsoft Kinect's data streams. At the last level, the approach estimates the average variation of the player's emotional state during gameplay.

Several sensors can be used in order to collect various kinds of affective signals and then, a predictor can be applied in any real-time setting for inferring engagement. Most of the proposed methods are based on physiological sensors or computer vision techniques. For the purpose of this game, we utilized Microsoft's Kinect v2.0.

Simultaneously, we also extract features related to players' cognitive and behavioral engagement based on the analysis of their interactions with the game. According to the literature, the dimension of behavioral engagement is defined as "focused activity on a task," with a typical measurement being time on task (Annetta et al. 2010; Koster 2013) while playing the video-game. Within the context of a game, the behavioral engagement of the student is measured by estimating his/her average time of responsiveness in all challenges of the game (e.g., the collection of treasure).

On the other hand, cognitive engagement is defined as "mental activity associated with the presented content" and is measured by successfully achieving the desired goal of the game, or by Ï and posttesting of outcomes (Koster 2013). Consequently, the cognitive student engagement is measured by estimating his/her average achieved score in all tasks of the game. It needs to be highlighted that each task can contain one or more challenges, and the final score of each task is influenced by the results of individual challenges. The score of each challenge has to do with the extent to which the required target was achieved. For example, in a task that the challenge is to cooperate, cognitive engagement can be measured by estimating the number of collected diamonds out of the total available.

Within the game, we extract features based on the analysis of specific gameplay events and their corresponding time-stamps in order to achieve a more targeted measurement of these two aspects of engagement. The extracted engagement components (i.e., affective, cognitive, behavioral) are given as input to an artificial neural network that is used for the automatic recognition of player's engagement. In order to train the network, we adopted a retrospective self-reports approach that is based on GEQ questionnaire and maps the players' answers to the engagement scale. The quantified form of the players' answers was used for labeling our data in the training procedure. For more details regarding the estimation of the student engagement, we refer the reader to our previous work (Psaltis et al. 2018). The overall engagement scheme is presented in Fig. 4.

## A testbed for prosocial skills: "Path of Trust"

For the purposes of this study, the game "Path of Trust" (PoT) was used as a testbed for the demonstration of the proposed multiadaptive approach. The framework for the game and adaptation is given in Fig. 5. This game has been designed to support game mechanics that allow the definition of learning objectives toward prosocial skills (Apostolakis et al. 2016a, b). In particular, PoT is an endless running game about two characters that need to cooperate in order to collect treasures within a maze while avoiding enemies and other hazards (Fig. 6). The two players take control of the two characters and set out to collect as many treasure points as they can within the designated time limit. The players' characters navigate a maze, structured by junctions and corridors. The player who is controlling the character moving

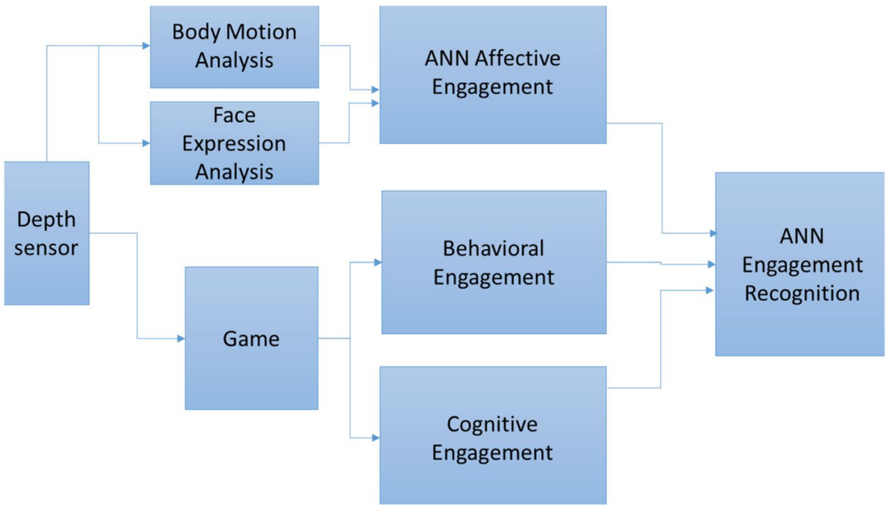



**Fig. 4** Schematic representation of the engagement mechanism

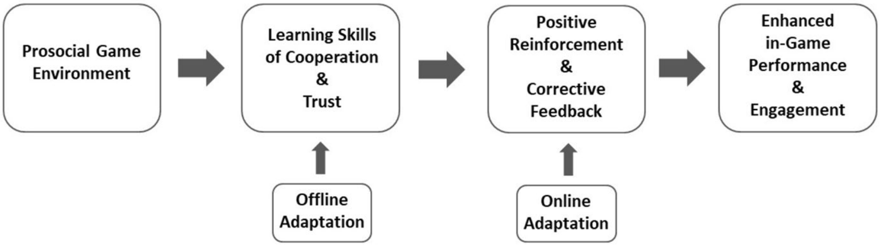



**Fig. 5** Framework for performance enhancement in prosocial games


**Fig. 6** The Path of Trust game: **a** Muscle character following directions within a maze, **b** The Guide character gives directions to Muscle

through the maze is referred to as the "Muscle," and is deprived of spatial awareness within the maze (i.e., the player can only see the area he/she is currently in). The other character is referred to as the "Guide" and uses a top-down map view to navigate both of them safely through the maze without being caught (as the Guide character is considered to sit on the shoulders of the Muscle character). The dungeon corridors are populated with items which can either be collected (upon touch) by the characters in order to score points, or be avoided, in the case that the item represents a hazard. The dungeon's junctions are special areas in which the characters' path can be altered by following up to three different directions (turning left, right or continuing forward).

As a narrative element in the "Path of Trust" storyline, the Guide is the only character with any knowledge about the items contained within the adjacent corridors. This feature is utilized to provide a memory-based mini-game designed to engage the player currently controlling the Guide, as he/she waits for the other player to navigate to the next junction. The Guide is supposed to pick which direction the two players should take next and make a proposition to the player controlling the Muscle. The Muscle is then supposed to trust in the Guide's suggestion and follow their directions, and cooperate by either touching the item in the corridor or avoiding it. A switching roles game mechanic allows players to actively swap characters, thus experiencing the cooperation from the other player's perspective. The game's ending condition is reached when any one of the two players manages to collect a certain number of points (six at minimum, in the default case). Furthermore, the game features a time limit and a set of different endings for the players to reach according to their performance. Considering the cooperation skill, players are expected to work as a team in a way that will allow them to finish the game with six (or more, in some cases) points each, thus demonstrating the skills necessary to appreciate following each others directions and understanding when they should sacrifice some of their own resources in order for the group to benefit in the long run (as they will accumulate more points as a team, as opposed to each player trying to gather all the points for themselves).

## Creating adaptable scenarios and game elements

In order to use the PoT game as our testbed for applying our adaptation approach, we created a set of adaptive in-game content. This content consists of scenarios and game elements that can be selected within certain instances in the game and are determined by the online and offline adaptation mechanisms. For the purposes of our study, we used the adaptation manager for prosocial skills (PAM) that have been described in "The adaptation manager" section. PAM is able to connect to PoT and support both the offline and online mechanisms for adjusting game content. The offline procedure determines the scenarios during the loading phase of the game, while the online procedure selects the game elements for engagement during the actual gameplay.

More specifically, for the offline adaptation, we created three dungeon layouts of increasing difficulty that correspond to different game scenarios. Each one of these layouts contains a different set of graphical assets and a number of GUI indicators such as increasing or decreasing the number of traps and portals or the chances of encountering junctions in which two or three similar, score-affecting items (e.g., two diamonds or three mummies) can be present. It is expected that increasingly more complex item distribution layouts will take significantly more time and effort on behalf of the players to complete with a favorable team outcome than others. This way, a player that may not cooperate and show her trust to her teammate, may exhibit prosocial behavior when a more difficult situation arises in the game. The scenarios currently supported within Path of Trust are the Egyptian Pyramid, the Knossos Labyrinth and Aztec Temple. These game scenarios are shown in Fig. 7.

For the implementation of the online adaptation, we created a set of in-game elements to act as positive reinforcement enhancers to the players. These elements are graphical representations commending the players for a job well done. The elements are depicted in Fig. 8 and consist of a plain "Well Done" message, a flashy "Congratulations!" animated pop-up icon, and a full-screen Fireworks Display. As players progress through the game, the online adaptation mechanism analyzes their engagement responses with respect to these elements and triggers one of them for administering positive reinforcement. For example, a player demonstrating strong engagement reactions toward seeing the "Fireworks Display" element, will increase

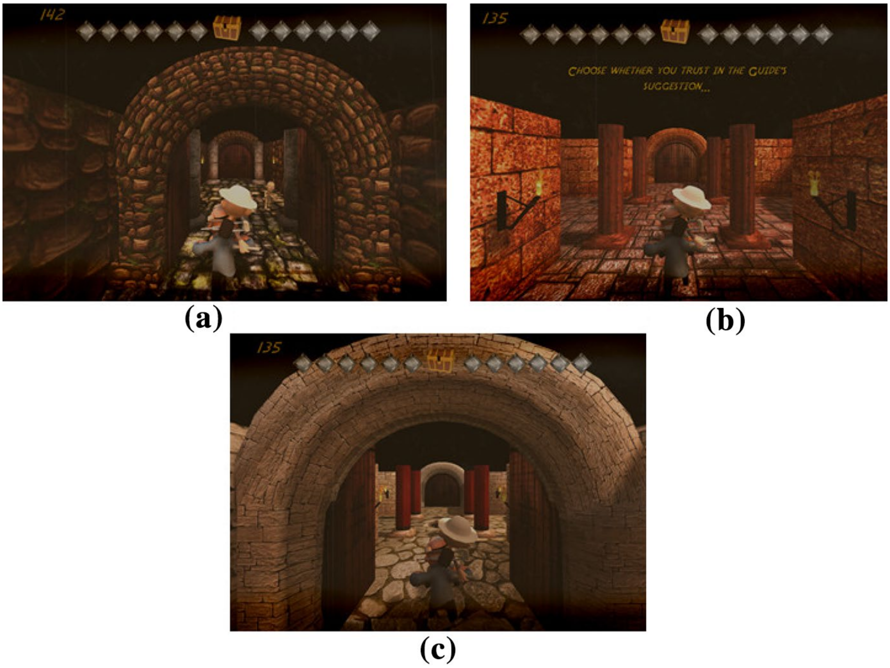



**Fig. 7** Adaptive scenarios in PoT adjusted by PAM offline adaptation: **a** Aztec Temple, **b** Egyptian Pyramid, **c** Knossos Labyrinth

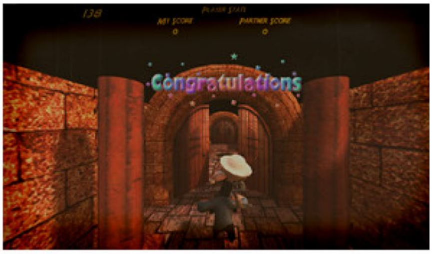
his/her chances of being commended with the same element during future positive reinforcement feedback from the game.

As described in the third section, we also included the use of corrective feedback as an engagement enhancer for the online adaptation. Therefore, any verbal communication of corrective feedback should be specific and relate to the action of the player has completed, to adequately communicate what the child is doing wrong. There are a variety of messages to convey to the user with respect to their chosen action in need of corrective feedback. These messages are expressed to the player by a special virtual character, i.e., a virtual tutor, or audio messages by a female or male coach (see Fig. 9). In any case, these messages should be clear and related to specific actions of the player within the game to adequately communicate what the child is doing wrong.

## Experimental results

To evaluate the proposed adaptation framework, we conducted hands-on experiments in a public primary school with 20 students, ranged in age from 7 to 10 years old, and we analyzed 30 game-play recordings. The main goal of the study presented in this paper was to examine whether the proposed adaptation framework contributes to the enhancement of student's performance in a prosocial game. We should


(a)

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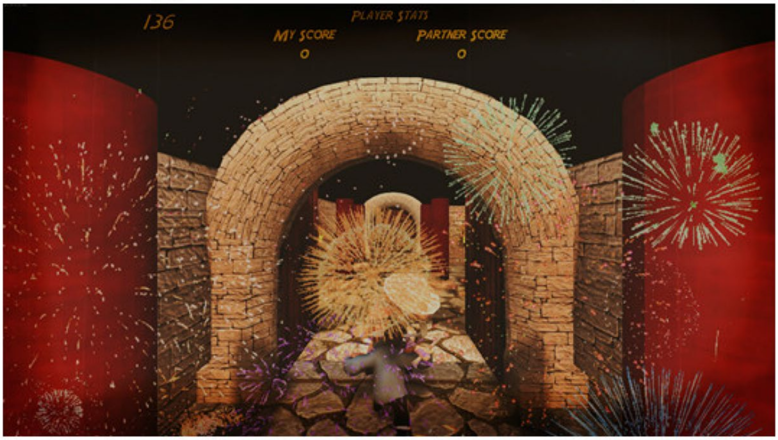
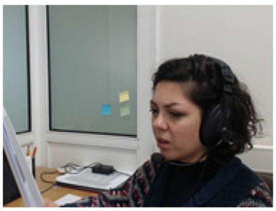


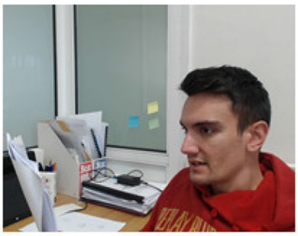

(c)

**Fig. 8** Positive reinforcement elements in PoT driven by PAM online adaptation: **a** typical well-done messages, **b** fancy congratulations message, **c** fireworks visual effects


(a)



(b)



(c)

**Fig. 9** Corrective feedback elements in PoT driven by PAM online adaptation: **a** artificial character coach pop-up icon, **b** female coach audio recording, **c** male coach audio recording

also clarify that the purpose of our experiment was not to examine the effects on students' behavior or learning after the game, and for this reason, we did not include any pretesting or posttesting procedures for the "Path of Trust" game.

More specifically, we formed 11 groups of students referenced as group A to group K, with two children randomly being paired with a second partner due to logistical reasons. Prior to this study, we prepared a login system in order to enable storing data on designated user profiles without compromising sensitive user data. Toward this end, we prepared numerous preregistered accounts and stored their credentials within the system login infrastructure. Each username/password combination was then handed out to participating children, who were allowed to randomly pick an illustrated card containing their personal account information. Both the internal game logging mechanism, as well as the PAM persistence mechanisms used the specified account names to update information on recurring players.

The actual outcome being measured in our study is the students' score, which is associated to possible game outcomes at the end of each game session. To clarify the paragraphs below, Table 1 summarizes the game's possible outcomes before presenting any observations for the offline and online adaptation mechanisms in Path of Trust.

## Offline adaptation

In this section, the researchers aim to evaluate the contribution of offline AI adaptation to the enhancement of students' performance in the game, i.e., whether the AI adaptation help students complete the game successfully. In other words, the goal is to prove that the proposed mechanism selects the most appropriate game conditions for each student based on the modeling of his/her ability in the prosocial game. As it will be showed, the scenario selected mostly by the adaptation mechanism, i.e., Scenario 1 (Egyptian Pyramid), leaded students to perform better in the game. To do so, the null hypothesis H0 is the following:

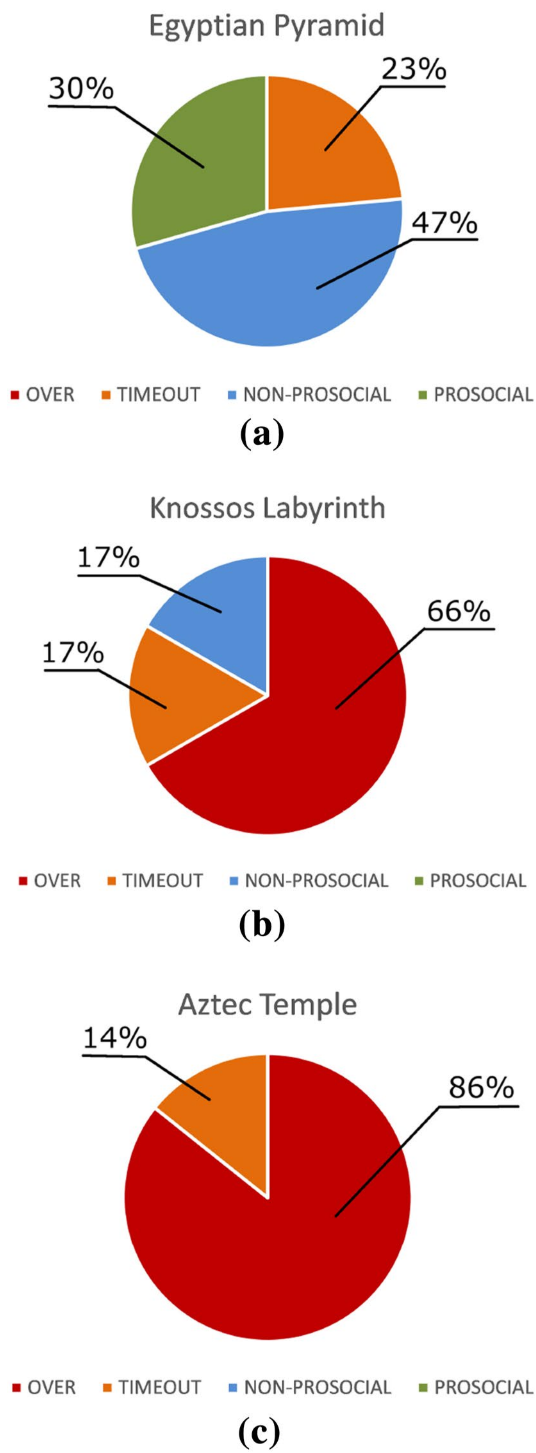
**H0** The most-selected game conditions do not enhance the performance of students.

Figure 10 presents the end-game results of students playing the game with different conditions, i.e., game scenarios. As we can easily see, in the case of Scenario 1, i.e., Egyptian Pyramid, 30% of game sessions ended with a Prosocial outcome, while 47% and 23% of game sessions ended with a Non-Prosocial and Timeout outcome, respectively. Players' progress in Knossos Labyrinth fared significantly worse, as approximately 67% of individual sessions ended with Over, while players in Aztec Temple did not manage to achieve any Prosocial or Non-Prosocial outcome. The players' performance with respect to the game's learning objective in cooperation

**Table 1** Game outcomes for PoT

| Game outcomes | |
|---|---|
| PROSOCIAL | Both players have captured 6 points or more |
| TIMEOUT | None of the two players have managed to capture six points or more during the designated time limit |
| NON-PROSOCIAL | One of the players has managed to capture six points or more |
| OVER | Instant game oyer |

**Fig. 10** Session game outcomes for each adaptive scenario



is reflected upon the offline adaptation's choice of appropriate game conditions. Hence, Egyptian Pyramid received substantially more play-time (17 individual sessions across all player groups) in contrast to Knossos Labyrinth (6 individual sessions) and Aztec Temple (7 individual sessions) levels.

Table 2 presents the mean normalized game score $S \in [0, 1]$ (0 for Over and 1 for Prosocial), as well as the standard deviation (STD) and error (SE) for the most selected scenario (Scenario 1: Egyptian Pyramid) and the two other scenarios (Scenario 2: Knossos Labyrinth and Scenario 3: Aztec Temple). The experimental results show that the students managed to achieve higher scores, i.e., mean value $m = 0.576$ and standard deviation $std = 0.307$, when played the game with the conditions of Scenario 1 (the most selected one) than with the conditions of the other two scenarios, i.e., mean value $m = 0.069$ and standard deviation $std = 0.149$. Results also indicate that the difference in the performance of students in these two cases was statistically significant, with $z = 2.589$, i.e., $z > 1.645$, and $p < 0.05$. In other words, the results support the alternative hypothesis $H_1$, i.e., the scenario that is selected mostly by the adaptation mechanism leads students to perform better in the game, and therefore, we can easily reject the null hypothesis H0.

## Online adaptation

In this section, the researchers focus on the online adaptation mechanism and investigate the role of corrective feedback (CF) and positive reinforcement (PR) adaptive elements in the successful completion of the game by analyzing the students' behavior immediately after receiving this feedback. The main goal here is to show that the recommendations produced by the online adaptation mechanism contributed to the enhancement of students' performance.

In this respect, students' in-game behavior can be classified into four categories: (i) PR-PR: Receiving positive reinforcement right after a positive reinforcement message (i.e., continuous successful actions), (ii) CF-PR: Receiving positive reinforcement right after a corrective feedback message (i.e., the players change their behavior after a CF message), (iii) PR-CF: Receiving corrective feedback right after a positive reinforcement message (i.e., the players do not follow the positive reinforcement message), and (iv) CF-CF: Receiving corrective feedback right after a corrective feedback message (i.e., the players continuously ignore or fail to follow the instructions of the game). Hence, in PR-PR and CF-PR cases, students follow the feedback produced by the system, i.e., there is finally a positive result, while in the cases of PR-CF and CF-CF, the system's feedback is not followed by the students, i.e., there is a negative result. In other words, the

**Table 2** Normalized scores for the most selected scenario (scenario 1) and the two other scenarios

| | Scenario 1 | Scenario 2 and 3 |
|---|---|---|
| Mean | 0.576 | 0.069 |
| STD | 0.307 | 0.149 |
| SE | 0.085 | 0.097 |

researchers here study whether students following the feedback provided by the system (i.e., Positive Reinforcement after either Positive Reinforcement (PR-PR) or Corrective Feedback (CF-PR)) had better performance in the game. Hence, the null hypothesis here is the following:

**H0** The game outcome is independent of students' in-game behavior toward the feedback provided by the system.

Table 3 shows the distributions of the four different categories of students' in-game behavior. As we can easily see, there are more PR-PR and CF-PR cases when there is a successful game outcome, i.e., a prosocial win, than in the three other game outcomes, with a frequency rate of 34.8% for both PR-PR and CF-PR. It is also worth mentioning that in the case of Timeout game outcome there are also many PR-PR and CF-PR cases, since this category includes students who were very close to succeed a prosocial win (i.e., they just needed one or two diamonds), but they finally run out of time. However, as we can see in Fig. 9, in the case of Prosocial win, the frequency of cases in which students followed the feedback provided by the system (i.e., PR-PR and CF-PR cases) is 69.6%, while for the three other cases of nonsuccessful game outcomes there is an average frequency of 43.46% ( Non-prosocial win: 34.9%, Timeout: 58%, Over: 37.5%).

To show that the final game outcome (i.e., Prosocial Win or Other, i.e., cases of nonsuccessful outcome) depends significantly on player's in-game behavior toward the feedback provided by the system, the researchers used a Chi-squared test (Fig. 11). More specifically, for the case of Prosocial Win (69.6% followed the feedback produced by the system, while 30.4% did not) and the other three nonsuccessful game outcomes (43.46% followed the feedback, while 56.53% received a corrective feedback after a PR or CF message, i.e., PR-CF or CF-CF cases) the Chi-squared test easily rejects the null hypothesis of independence with $p = 0.00035$, i.e., $p < 0.005$. This result shows that the frequency of CF-PR and PR-PR cases (i.e., when students follow the feedback produced by the system) in a game session significantly affects the final outcome of the game, and as a result, the feedback produced by the AI mechanism facilitates students to enhance their in-game performance.

**Table 3** Distribution of in-game muscle player behaviors and game outcomes

| Game outcomes | PR-PR (%) | CF-PR (%) | PR-CF (%) | CF-CF (%) | Total (%) |
|---|---|---|---|---|---|
| Successful game outcome | | | | | |
| Prosocial win | 34.8 | 34.8 | 26.1 | 4.3 | 100 |
| Non-successful game outcomes | | | | | |
| Non-prosocial | 27.9 | 7 | 20.9 | 44.2 | 100 |
| Timeout | 32 | 26 | 28 | 14 | 100 |
| Over | 25 | 12.5 | 37.5 | 25 | 100 |

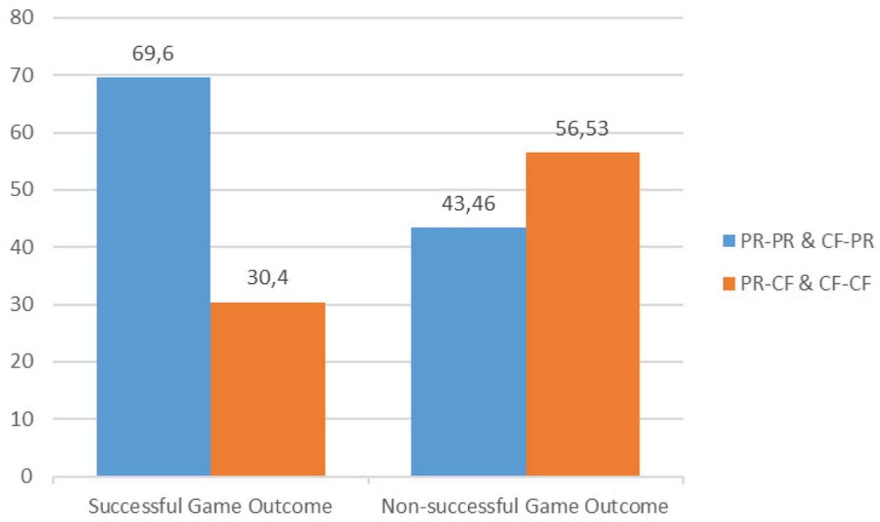



**Fig. 11** Results of PR-PR/CF-PR (i.e., students followed the feedback provided by the system) and PR-CF/ CF-CF (i.e., students did not follow the feedback provided by the system) cases for successful and nonsuccessful game outcomes respectively

## Conclusions and discussion

In this paper, the researchers present a novel adaptation framework, which aims to improve personalization and enhance student's performance in prosocial video games. The proposed framework provides intelligent adaptation and personalization through the modeling of student's ability and engagement level. The two different adaptation mechanisms—the offline and online adaptation—process different types of information in order to better adjust the game to the personal needs of each student. The experimental results indicate that the multiadaptive approach presented in Fig. 5 is able to provide effective guidance and increase player performance in attaining the learning objectives of a prosocial game. More specifically, a small-scale experiment was carried out in a public primary school and showed that there were statistically significant evidence supporting the aforementioned hypothesis (i.e., the adaptation framework contributes significantly toward the enhancement of students' performance) in both cases, for offline and online adaptation.

Although the present study focuses on prosocial games for cooperation and trust, the proposed adaptation framework is generic and can be easily applied to a variety of serious games in education. Based on the theoretical grounds of educational psychology, the proposed method measures student engagement, by exploiting real-time engagement cues from different input modalities (Psaltis et al. 2018), and proposes an online mechanism for the selection of the most appropriate dynamic element in a game based on the creation of student's engagement profile. On the other hand, by exploiting the efficiency of the Elo rating model, a novel offline adaptation mechanism is proposed, which enables the estimation of the rating of a student's ability in an educational video game (as well as the estimation of the rating of each game scenario) and the automatic adjustment of game's difficulty according to the personal needs of each student. To this end, the researchers believe that the proposed offline adaptation mechanism could be easily used for modeling student's ability level beyond the context of prosocial skills and the efficient personalization of an educational game. In this study, it is considered that each prosocial game is designed so that it can model one prosocial learning objective and measure the degree of its accomplishment. For this reason, the study of different techniques for measuring prosocial skills is out of the scope of this paper; however, one could investigate in the future the idea of combining various techniques for measuring students' prosocial skills for a more accurate estimation of students' prosocial ability.

Regarding the limitation of the proposed adaptation framework, it is important to note that the adaptation manager presented in this paper is not able to capture individual player preferences about game content and does not consider multi-player cases where common preferences have to be pointed out. Another important aspect worthy to mention is that while online learning algorithms provide improved personalization capabilities they require, in general, a sufficient number of player data, i.e., game plays, to converge. This is a crucial issue that one has to consider since a large amount of game data from multiple users may be hard to collect. As a final remark, multilayered adaptation schemes generally suffer from interoperability problems since any game that uses them has to provide the necessary adaptive content for each layer.

In the future, the game can be employed within the framework of a model, similar to the one presented in Fig. 1, for teaching and learning social and emotional skills (e.g., properly instructing, demonstrating the necessary skills prior to the game session and generalizing during postsession debriefing with the teacher). This is also supported by previous researches, which have shown that effective programs need to provide repeated opportunities to students to practice new skills and behavior within each program structure and beyond to real-life situations (C.A.S.E.L 2013; Durlak et al. 2011).

Other future directions stemming from this work might include adding more layers to game adaptation in order to capture even more aspects of player behavior and also, study the effects of each layer on prosocial games. Another interesting direction could be the addition of group adaptation capabilities that can model joint player preferences and enhance the performance of groups in prosocial games.

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