Offline and Online Adaptation in Prosocial Games

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Abstract*—Personalization and maintenance of high levels of engagement still remain two of the main challenges in the design of serious games. Towards this end, in this paper we propose a novel adaptation approach for both online and offline adaptation in prosocial games. In this paper, we describe the implementation of an artificial intelligence driven adaptation manager, whose purpose is to direct players towards game content the players are most likely to enjoy (measured in their engagement responses). As a consequence, we demonstrate how the adaptation manager can be used to increase the chances of players attaining the game's specific prosocial learning objectives.. Each mechanism (offline and online) processes different information about the player and concerns different types of factors affecting engagement and prosocial behavior. More specifically, the online mechanism maintains a player engagement profile for game elements related to the provision of Corrective Feedback and Positive Reinforcement, in order to adapt existing game content in real time. On the other hand, off-line adaptation matches players to game scenarios according to the players' prosocial ability and the game scenarios' ranking. The efficiency of the proposed adaptation manger as a tool for enhancing students' prosocial skills development is demonstrated through a small scale experiment, under real-conditions in a school environment, using the prosocial game of Path of Trust.

Keywords*—*adaptation; serious games; engagement; prosociality

I. INTRODUCTION

Modern digital games, especially those designed for educational purposes, need to avoid the one-size-fits-all game design principle by providing personalization capabilities to better suit the preferences of their players. For most games, these approaches often include an estimation of the skill level of the player that is determined by the accomplishment of certain in-game tasks. A player's ability model is updated using game event information or statistics, and a set of game parameters is adjusted in order to satisfy the individual's performance and eventually offer a personalized virtual experience to the player [1]. A major area of application for player ability modelling is the dynamic difficulty adjustment (DDA) game adaptation, within which the difficulty level of a game is properly altered to provide the necessary challenge for optimizing the player's entertainment [2]. Recent works in DDA include procedural content generation [3], affective computing [4] and online user training [5].

DDA mechanisms are most commonly encountered in single player games. Player ability modelling in competitive multiplayer games typically occurs in situations involving matchmaking between players. The most acknowledged example of such a matchmaking mechanism is the Elo rating system that was initially used to measure the ability of players in chess competitions [6]. In [7], a Bayesian skill rating system is presented, which can be viewed as a generalization of the Elo system based on approximate message passing in factor graphs. Iida et al. [9] proposed an application of the game refinement theory to a class of multi-person incomplete-information games. On the other hand, an approach to organizing units is described in [10], by learning the effectiveness of a formation in actual play, and directly applying learned formation according to the classification of the opponent player. In addition, Bio-inspired computational algorithms are effectively employed in [11], in order to develop educational games for learning. More recently, Hussaan et al. [12] proposed a set of models that allow the user to create coherent profiles, which are automatically updated during the game session.

In their quest for finding new and effective means of promoting learning through digital games, serious game developers have turned their focus on artificial intelligence research. Their central assumption is that adapting game content to certain aspects of player behaviour can aid his/her effort for completing the game and thus, assist in learning specific types of skills. Common types of skills typically encountered in serious games include social, communication, psychological, reading, language or music skills [13]. The special case of monitoring physical activity has also met the interest of both the serious and leisure gaming industry, and therefore, games adaptable to body movements have been developed for both entertainment and rehabilitation purposes [1][14][15].

In this paper, we propose a novel adaptation approach for providing intelligent adaptation and personalization in prosocial games, i.e., games in which the main characters (and therefore, players controlling them) model and carry out prosocial behaviors. Prosocial behavior refers to a type of social behavior that is intended to benefit other people, e.g., helping, sharing, cooperating, etc., and/or society as a whole, e.g., donating, volunteering, etc. [16]. The proposed adaptation approach supports both offline and online adaptation to provide prosocial games with better personalization capabilities. The two proposed mechanisms (offline and online) process different information about the players and aim to personalize the prosocial games towards maximizing the players' engagement during gameplay, or select appropriate game settings, based on players' profiles, beforehand.

The remainder of this paper is organized as follows: In Section II the authors' prosocial game Path of Trust is briefly presented. Section III outlines our prosocial adaptation manager and Section IV describes the experimental procedure that was followed. Finally, the experimental results of our study are given in Section V, while conclusions are drawn in Section VI.

II. The Prosocial Game

Path of Trust is an endless running game about two characters having to cooperate in order to navigate a maze and collect treasures while avoiding enemies and other hazards in the process (Fig. 1). The game features a single player mode that supports Prosocial Learning Objectives (PLOs) with respect to the prosocial skill of evaluating trustworthiness of the NPC character, while the two-player mode of the game focuses on teaching the benefits of cooperation [17][18]. In the remainder of this text we will focus on the multi-player version of the game. In this version of the game, 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, as is shown in Fig. 2. The player who is controlling the character moving through the maze is referred to as "the Muscle" (Fig. 1), and is deprived of spatial awareness within the maze (i.e., the player can only see the area he/she is currently in), while the other character referred to as "the Guide", uses a top-down map view to navigate both of them (as the Guide character sits on the shoulders of the Muscle character) safely through the maze without being caught. The dungeon corridors are populated by items, which can either be collected (upon touch) by the characters to score points or, in case the item represents a hazard, need to be avoided. 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 on the items contained within the adjacent corridors. This element is utilized to provide a memory-based mini-game designed to engage the player currently controlling the Guide, as they wait for the other player to navigate to the next Junction. The Guide is supposed to pick which direction the duo 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.

As an end-game condition, the game will end when any one of the two players reaches a designated number of points (six, in the user study). 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 other's 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).

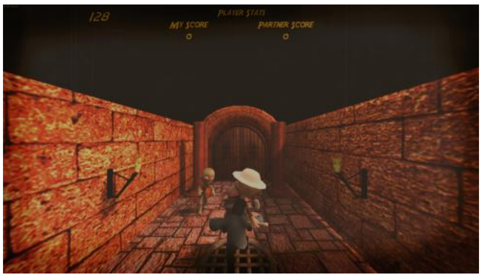


Fig. 1. The "Path of Trust" game.

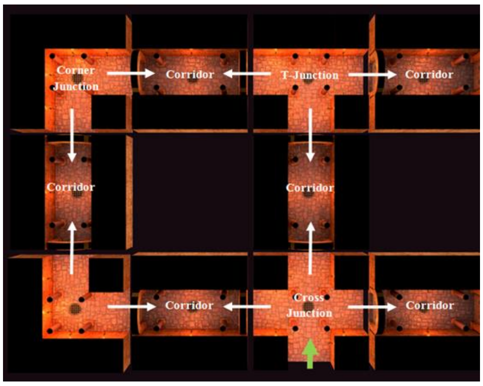


Fig. 2. Junction and Corridor dungeon tile types making up the Path of Trust map maze. The bold green arrow indicates entry point for the characters. The white arrows indicate possible navigation paths.

Fig. 3. The screen of the Guide in Path of Trust.

III. 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 beforehand, in the loading phase of the game. These two mechanisms aim to personalize the prosocial games towards 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 input 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 to best tailor the game to that player's preferences in a way that aims to maximize their engagement. In the paragraphs that follow, more detailed information about the two mechanisms is provided.

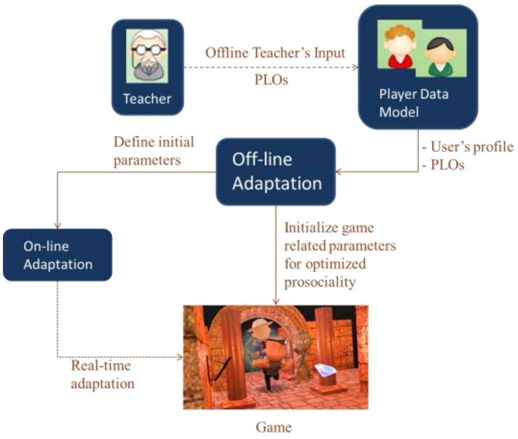


Fig. 4. Schematic representation for the offline adaptation mechanism

A. Offline Adaptation

Offline adaptation is realized in the loading phase of the game, as shown in Fig. 4. Its purpose is to select game conditions that are expected to drive the player towards 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 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 her prosocial ability level. This scenario is then used to initialize the game.

More specifically, the ability ranking system developed is based on the well-known Elo rating system, which was initially proposed by Arpad Elo [6]. 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 can determine the proper scenario for the player, namely, the one that preserves those conditions that maximize his or her prosocial ability.

B. Online Adaptation

Online adaptation is realized during actual gameplay as shown in Fig. 5. Its purpose is to select the proper game elements that contribute to the enhancement of the player's engagement in pursuing a prosocial objective, i.e., cooperation or trust. These game elements concern the standard pedagogical practice of expressing positive reinforcement and corrective feedback on a student's performance:

- *Positive reinforcement* is the process of strengthening a person's behaviour as a consequence of applying a stimulus.
- *Corrective feedback* provides instructions to players to correct their behaviour 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 behaviour 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.

Path of Trust offers a pool of elements (e.g. text messages, sounds or graphics) realizing positive reinforcement or/and corrective feedback. Online adaptation considers real-time player data concerning player's engagement estimation during specific time intervals in the game. Hence, the player's engagement estimation is vital within the context of prosociality, due to the concept's gamification as in-game tasks for building up a set of predefined abilities.

Since engagement is a multifaceted phenomenon with different dimensions, i.e., behavioral, cognitive and affective, we propose the modeling of student engagement using real-time data from both the user and the game. More specifically, and in using the Kinect for Xbox One controller as the primary means of interfacing with the game, we apply body motion [19] and facial expression analysis to extract player joint skeleton and facial Action Unit (AU) data. These features are then fused to identify the affective state of players [20], representing the affective dimension of player engagement. We then also extract features related to players' cognitive and behavioral engagement based on the analysis of their interactions in-game. Towards this end, we extract features based on the analysis of specific game-play events and their corresponding time-stamps in order to achieve a more targeted measurement of these two aspects of engagement. 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 [21][22] while playing the video-game. 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 pre and post testing of outcomes [21]. After the extraction of these features (affective, cognitive, behavioral), an artificial neural network is used for the automatic recognition of player's engagement.

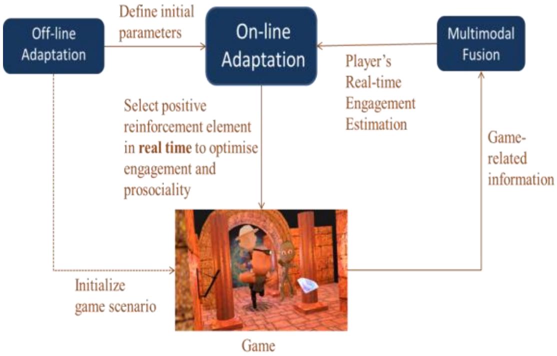


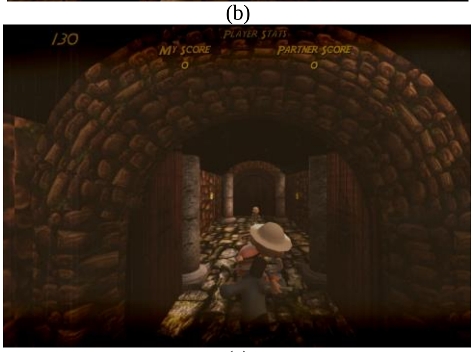
Fig. 5. Schematic representation for the online adaptation mechanism

C. *Offline / Online Adaptation in Path of Trust*

As previously mentioned, offline adaptation within the context of the PAM requires the game developers to define a set of scenarios, i.e. varying levels of challenge as to the way the prosocial skills are being tested. Therefore, in order to challenge players' skills, more challenging dungeon layouts are required. This is achieved within Path of Trust, by increasing the number of traps and portals, while simultaneously decreasing 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 favourable team outcome than others. As a result, we created three, increasingly difficult dungeon layouts, and corresponded each one to a different game scenario for the offline adaptation mechanism of the PAM to choose from. To indicate these changes to the players, we created different sets of graphical assets and GUI indicators for each scenario, thus ending up with three different levels to support variety for the game as players progress their skills abilities. The levels currently supported within Path of Trust are the Egyptian Pyramid, the Knossos Labyrinth and Aztec Temple levels. The resulting game scenarios are shown in Fig. 6.

(a)

(b)



(c)

Fig. 6. Path of Trust scenarios supporting PAM offline adaptation mechanism: a) Egyptian Pyramid (minimum challenge), b) Knossos Labyrinth and c) Aztec Temple (maximum challenge).

On the other hand, online adaptation within the context of the PAM requires the game developers to define a set of elements. Elements can be anything within the game, from specific sound effects to graphics and GUI elements. We considered elements within Path of Trust to be specifically tied to manners through which the game presents positive reinforcement or corrective feedback to the players, in response to their performance after a game task has been completed.

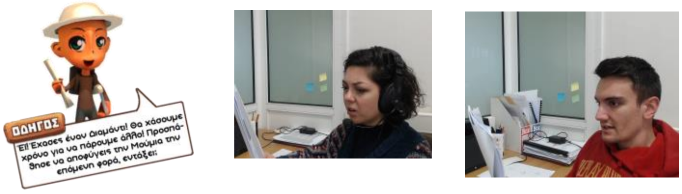
(a)

(b)

(c)

Fig. 7. Path of Trust Positive Reinforcement elements supporting PAM online adaptation mechanism: a) Well Done; b) Congratulations!; c) Fireworks Display.

We defined three different in-game elements for presenting Positive Reinforcement enhancers to the players. These are all graphical representations of the game commending the players for a job well done. The actual elements are depicted in Fig. 7, namely a plain "Well Done" message, a flashy "Congratulations!" animated pop-up icon and a full-screen Fireworks Display. As players progress through the game, online adaptation mechanisms will analyse player engagement with respect to these elements and trigger one of these elements for administering positive reinforcement. For example, a player demonstrating strong engagement reactions towards seeing the Fireworks Display element will increase his/her chances of being commended with a Fireworks Display during future Positive Reinforcement feedback from the game.



(a) (b) (c)

Fig. 8. Path of Trust Corrective Feedback elements supporting PAM online adaptation mechanism: a) Guide Character Coach pop-up icon indicator; b) Female Coach audio recording session; c) Male Coach audio recording session.

For Corrective Feedback, we followed a different approach, seeing how the elements should contribute towards the player understanding their mistakes and trying again in order to succeed. 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 can be conveyed by a guide character, i.e., a virtual tutor, or audio massages by a female or male coach (see Fig. 8).

TABLE I. POSSIBLE GAME OUTCOMES

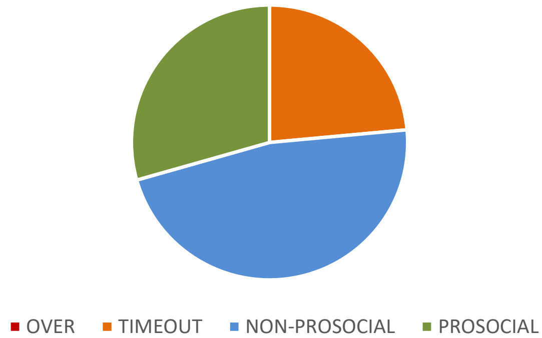
Outcome	Description
PROSOCIAL	Both players have captured 6 points or more
TIMEOUT	None of the two players have managed to capture six points or more during the designated time limit
NON-PROSOCIAL	One of the players has managed to capture six points or more
OVER	Instant game over

IV. EXPERIMENTAL RESULTS

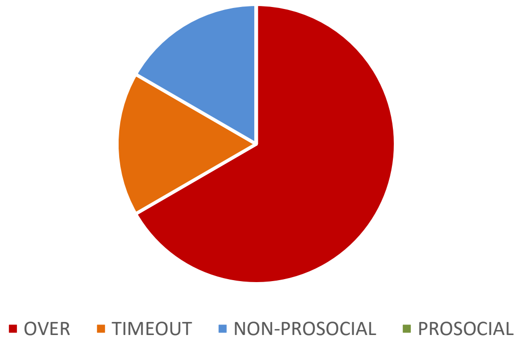
A. Procedure

Participants in our study were a total of 20 children ranged in age from 8 to 9 years old. In total, 11 groups (referenced as group A to group K, with two children randomly being paired with a second partner due to logistical reasons) completed the entire session. Prior to this study, we prepared a login system in order to enable storing data on designated user profiles without compromising sensitive user data. Towards this end, we prepared numerous pre-registered 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.

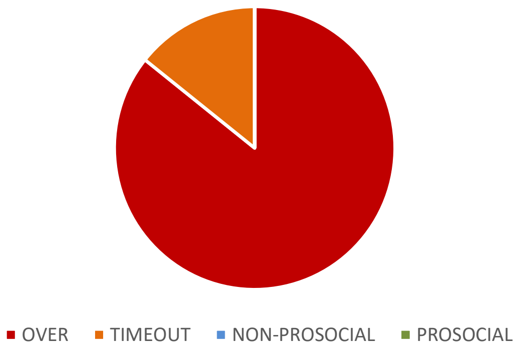
Our observations with respect to the game's adaptation efficiency have been associated to the possible game outcomes at the end of each game session. To clarify the paragraphs below we summarize in Table I the game's possible outcomes before delving deeper into our observations on offline and online adaptation mechanism in Path of Trust.



(a) Egyptian Pyramid



(b) Knossos Labyrinth



(c) Aztec Temple

Fig. 9. Individual game session outcomes per Path of Trust scenario

B. *Offline Adaptation*

Our study has confirmed our approach to increase difficulty of the three dungeon layouts. The end-game results demonstrate an efficient distribution of challenge across the three game scenarios for offline adaptation, as players managed to achieve a PROSOCIAL outcome in 5 individual game sessions in Egyptian Pyramid, while 8 sessions ended with a NON-PROSOCIAL and 4 sessions with a TIMEOUT outcome. Players' progress in Knossos Labyrinth fared significantly worse, as approximately 67% of individual sessions ended with players being felled by a trap (OVER), while players in Aztec Temple did not manage to record a single session with 6 points or more earned for an individual partner (i.e., no PROSOCIAL or NON-PROSOCIAL outcomes achieved, despite the latter being quite easily attainable, as described in the previous paragraph). The players' performance with respect to the game's PLO in cooperation is reflected upon the offline adaptation's choice of appropriate scenarios for both players, as the easiest level, 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. The end-game outcome results are graphically depicted in Fig. 9.

C. *Online Adaptation*

We approached our analysis of the online adaptation comparing player adherence to the online Corrective Feedback (CF) / Positive Reinforcement (PR) messaging mechanisms towards measuring the final game outcome. In this analysis, we are interested in analysing player behaviour immediately after receiving feedback from the game, thus monitoring their next action through the next feedback received. In this respect, player in-game behaviour can be distinct into four categories, as shown in Table II.

TABLE II. POSSIBLE BEHAVIOR

Behavior	**Description**
PR-PR	Receiving Positive Reinforcement right after a Positive Reinforcement message
CF-PR	Receiving Positive Reinforcement right after a Corrective Feedback message
PR-CF	Receiving Corrective Feedback right after a Positive Reinforcement message
CF-CF	Receiving Corrective Feedback right after a Corrective Feedback message

On the other hand, as can be seen in Table III, players who achieved PROSOCIAL outcomes demonstrated a significant capacity for adherence to the game's Positive Reinforcement / Corrective Feedback, taking significantly less time (shown by the number of consecutive feedbacks given by the game as a response to the Muscle player's actions) to reach the desired outcome and following up on previous game feedback with commendable action (e.g., receiving Positive Reinforcement after their previous action was addressed by either a PR or CF message) during approximately 70% of the times (PR-PR, CF-PR), while following up twice with non-commendable action to a CF message (CF-CF) in just approximately 4% of the time.

Some similarity can be observed for players managing a NON-PROSOCIAL or TIMEOUT outcome, demonstrating a significant overall amount of time taken to achieve these outcomes (i.e., shown by the overall number of consecutive feedbacks given, clearly in contrast to the PROSOCIAL case). In the first case, a very strong indicator of player ignorance to feedback instructions can be seen in players responding to the previous PR or CF message with non-commendable action (PR-CF, CF-CF) in approximately 65% of the time, which indicates a stark contrast to playthroughs ending in a PROSOCIAL outcome. On the other hand, TIMEOUT cases demonstrate an overall evenly distributed pattern of actions, which indicates a slight preference of players towards being positively rewarded (58%) after a certain action was taken in response to the message previously received (PR-PR, CF-PR). This can be explained by closely observing the game logs for these playthroughs, in which TIMEOUT outcomes were reached after a significant number of turns had passed, and with player scores being mostly evenly distributed (e.g, 4-5, 3-3, 4-3 etc.) but time was not enough for players to achieve the PROSOCIAL outcome. In other words, players demonstrated significantly more adherence to the prosocial objective of being collaborative than players who ended up with a NON-PROSOCIAL outcome, but yet rather significantly lower capacity for continuously doing so, as in the PROSOCIAL outcome attaining groups. This capacity is also taken into consideration towards determining player PLO rankings for offline adaptation, as there is some difference to the TIMEOUT occurring while players have a score of 5-5 or 1-3, yet both cases could have gone either way if the game had infinite time to reach the designated number of points.

These outcomes, in conjunction to the ones in the PROSOCIAL case in Table III, demonstrate how players tend to better cooperate when adhering to the game's PR/CF messages, tailored personally to their engagement preferences. Players actively ignoring these messages tend to experience much more difficulty, as they are more prone to underachieve (e.g., NON-PROSOCIAL outcome) or, risk falling into a trap (OVER outcome), which usually occurs when players demonstrate a clear preference to follow up on PR/CF messages with non-commendable action (PR-CF, CFR-CF in 62.5% of the times, especially considering the limited game time due to the instant game over a trap object brings about to the game).

In total, by looking over the amount of players following up on CF messages with corrective action (e.g. CF-PR), we see a clear link towards maximizing the likelihood of achieving the desired PLO outcome, and even more so, much faster than players choosing to ignore the CF and act out on their own volition in contrast to the desired outcome (CF-CF). Furthermore it is almost certain that players who continuously ignore CF (e.g. CF-CF) will end up underachieving, (NON-PROSOCIAL, OVER) in contrast to those that demonstrate a higher capacity for taking corrective action (TIMEOUT). These conclusions can be summed up in Fig. 10. These results demonstrate a promising "raw" potential for game adaptation to help players in achieving prosocial outcomes through continuous gameplay of adaptable prosocial games over time. To achieve player adherence to the in-game instructions, a prosocial model for teaching and learning social and emotional skills can be employed prior (e.g. properly instructing and demonstrating the necessary skills) as well as after the game (e.g. generalizing during post-session debriefing with the teacher). We show in this work that adaptable PR/CF elements can contribute towards maximizing the likelihood of attaining PLO outcomes, which in turn can help an offline mechanism match player groups to the proper amount of challenge in order to help players advance their learning.

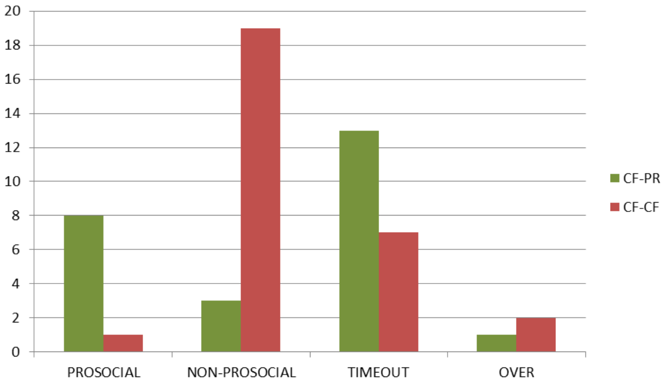


Fig. 10. Indicative player response to Corrective Feedback messages. Chart demonstrates relation between outcome of the game (Prosocial, Non-Prosocial, Timeout, Over) and following up on Corrective Feedback with proper action (PR) and non-commendable action (CF) across the amount of interactions.

TABLE III. DISTRIBUTION OF IN-GAME MUSCLE PLAYER BEHAVIOURS AND GAME OUTCOMES PER INDIVIDUAL SESSION.

PROSOCIAL					
	PR-PR	**PR-CF**	**CF-PR**	**CF-CF**	**Total**
No. of instances	8	6	8	1	**23**
Percentage	~34,8%	~26,1%	~34,8%	~4,3%	**100%**

NON-PROSOCIAL					
	PR-PR	**PR-CF**	**CF-PR**	**CF-CF**	**Total**
No. of instances	12	9	3	19	**43**
Percentage	~27.9%	~20,9%	~7%	~44,2%	**100%**

TIMEOUT					
	PR-PR	**PR-CF**	**CF-PR**	**CF-CF**	**Total**
No. of instances	16	14	13	7	**50**
Percentage	32%	28%	26%	14%	**100%**

OVER					
	PR-PR	**PR-CF**	**CF-PR**	**CF-CF**	**Total**
No. of instances	2	3	1	2	**8**
Percentage	25%	37,5%	12,5%	25%	**100%**

V. CONCLUSIONS

In this paper we presented two distinct mechanisms, namely, offline and online adaptation, aiming to enhance prosocial behavior in children in Path of Trust game. We aim to follow-up on the experimental results analysis with a thorough investigation of player real-time engagement indications, and how these can be linked towards the different outcomes attained by the group. Towards this end, a fully adaptable version of the game (with PR/CF strategies developed for the player controlling the Guide character in a similar fashion) will be developed.

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