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Article

CogniChallenge: Multiplayer serious games' platform for cognitive and psychosocial rehabilitation

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Abstract

Information and communication technologies, such as serious games, have contributed to addressing the gaps in cognitive rehabilitation for individuals with acquired brain injury (ABI), particularly in the context of the COVID-19 pandemic. Although there are effective software programs and games available for cognitive rehabilitation, they have certain limitations. Most current programs have difficulties to adapt to individual performance, a critical factor in promoting neuroplasticity. Additionally, these programs typically only offer single-player modes. However, patients experience difficulties in social interactions leading to social isolation. To overcome these limitations, we propose a novel platform called CogniChallenge. It introduces multiplayer serious games designed for cognitive and psychosocial rehabilitation, offering competitive and cooperative game modes. This platform facilitates engagement with other patients, family members, caregivers, and virtual agents that simulate human interaction. CogniChallenge consists of three games based on activities of daily life and incorporates a multi-agent game balance system. Future research endeavors will focus on evaluating the usability and gameplay experience of CogniChallenge among healthcare professionals and individuals with ABI. By proposing this innovative platform, we intend to contribute to expanding the application of serious games and their potential to solve problems and limitations in the specific field of cognitive rehabilitation.

1. Introduction

New technological advances in computerized platforms and gamification are increasingly being applied to the field of cognitive rehabilitation (CR). It is defined as a systematic, functionally oriented service of therapeutic activities based on the assessment and understanding of patients' brain-behavioral deficits [1]. The advances in technology has contributed, in recent years, to minimize or overcome some gaps in access to traditional rehabilitation treatment, namely the restrictions imposed by disability, geographical barriers, financial difficulties, and time constraints

[1]. The pandemic of COVID-19 and social isolation that created difficulties in providing CR in-person settings contributed to reinforce the benefits of these interventions [2]. Individuals with acquired brain injury (ABI), any type of brain injury that happens after birth and is not associated with congenital disorders, degenerative disorders, or brain trauma at birth [3], were at higher risk of COVID-19 infection due to their cognitive and behavioral limitations, which may hinder their ability to take preventive measures. Additionally, those with multiple comorbidities associated with ABI are even more vulnerable to the effects of infection [4]. In Portugal, it is estimated that 91% of stroke survivors who were indicated for rehabilitation had to suspend it or did not even start it. However, the delay in this process is associated with a higher probability of long-term disability [5].

In this context, computer-based cognitive training offers several advantages in CR. It allows for remote customization and administration of rehabilitation programs; facilitates intervention planning; provides immediate feedback; enables performance monitoring and real-time feedback; enhances individual autonomy in the rehabilitation process, and promotes motivation and ecological validity of the activities developed [1], [6]. Existing cognitive software programs focus on cognitive stimulation (e.g., NeuronUp), training (e.g., Cogmed, CogniPlus, SOCIABLE), or rehabilitation (e.g., FestKits) [7]. These programs have been widely adopted and research has confirmed their effectiveness [8]–[10] . However, they vary in terms of functions, goals, and characteristics. Some programs allow for defining training goals and customizing parameters (e.g., session duration and frequency), but others include standardized training sessions that lack the ability to modify or adapt treatments to patients' cognitive profiles (e.g., Cogmed). Additionally, most of these tools lack continuous and adaptive adjustment of task difficulty based on the performance of patients, which is crucial for promoting neuroplasticity [1]. For example, individuals with ABI who used RehaCom, one of the most widely studied cognitive training gaming platforms, had to rely on their therapists to customize sessions [11].

Most of these games have been developed primarily for single-player. However, some patients manifest difficulties in processing and generating social behaviors (e.g., appropriate response to people's reactions, interpretation of feedback from others, inability to initiate speech or maintain the topic in conversations), with implications on family, social, and workplace relationships [12], [13]. These difficulties can lead to reduced social activity, loss of relationships, and consequently social isolation [14]. Therefore, while these patients may benefit from social interaction for their recovery, it is also recognized that some patients may also have difficulties in these interactions due to their specific condition, which can be considered when developing new resources and interventions. We only found one platform that included this social dimension, the SOCIABLE platform, a computer-based cognitive training and social activation program focusing on the cognitive, affective, and functional abilities of elderly people, patients with mild cognitive impairment, and patients with Alzheimer disease [15]. This platform is no longer available. However, the focus on psychosocial adjustment appears to be an integral component of the rehabilitation process, as found by a recent study, psychosocial functioning (e.g., social and recreational activities) mediates changes in motor (explaining 81.3% of motor improvements), and cognitive (explaining 70.7% of cognitive improvements) function during neurorehabilitation [16].

One of the main considerations when dealing with ABI is to develop rehabilitation services that addresses the clinical, emotional, and social needs of patients with ABI and their family, from initial hospitalization to reintegration into their communities [17]. To address these comprehensive needs, we present a proposal of a multiplayer serious gaming platform for cognitive and psychosocial rehabilitation, based on the use of serious games (SG) with collaborative and competitive characteristics to promote social interactions beyond CR. The use of SG has been applied to the CR domain with increasing evidence in favor of its effectiveness [11], [18]. Furthermore, digital games worldwide are one of the most popular entertainment media [19] and the confinement measures of the COVID-19 pandemic led to an increase in the use and duration of video games [20]. This may have contributed to reinforce the social role of video games not only as a form of easy entertainment at home, but also to promote social interaction, connecting people through a shared experience [21].

The proposed system differentiates itself from existing platforms by incorporating an intelligent agent system, enabling users to play games with other users (e.g., patients with ABI, family, and friends) or computer opponents, contributing to promote social interactions and a context to practice interpersonal skills. Additionally, the system includes a multi-agent game balancing system, ensuring that users at different stages of rehabilitation are motivated throughout the process with balanced and appropriate games and challenges.

2. Technical Background

2.1 Multi-Agent Systems

Multi-Agent Systems (MAS) have been studied as a field since 1980 and gained wide recognition in the mid-1990s. Since then, interest has continued to grow due to the conviction that agents are a suitable software paradigm to exploit the possibilities presented by massive, open distributed systems like the internet or even real-life examples like stock market [22], healthcare [23] or even board games [24]. MAS seem to be a natural metaphor for understanding and building a wide range of what we might call artificial social systems [25]. MAS are systems composed of multiple independent computer elements that interact with each other, known as Agents, which are entities oriented to achieve a certain goal by observing, evaluating their environment, and performing an action. Agents are computer systems capable of acting autonomously, depending on how their behaviors and interactions with the environment are defined. They are even capable of interacting with other agents or players — not only exchanging data but participating in simulations of social activities that we all perform in our daily lives. The interest in MAS is largely based on the assumption that many real-world problems are best modelled using a set of agents rather than a single agent. The reason that agents are such an important aspect is that they simulate learning behaviors. They can learn and adapt their behavior, which is one of the most important features of intelligence using positive and negative reinforcement [26]. These agents can give us answers to maximization problems and be used as simulations. When designing MAS, it is impossible to predict all potential situations an agent may face and to optimally develop an agent's behavior in advance, especially because when an agent interacts with another agent the possibilities increase exponentially. Therefore, agents must learn from their environment and adapt to it, especially in a multi-agent context. This is where Multi-Agent Learning is used to integrate Machine Learning Techniques into a MAS to create these adaptive agents. The most popular Multi-Agent Learning technique, and the one we used during the development of this platform is Reinforcement Learning.

2.2 Reinforcement Learning

Reinforcement learning provides a normative description, based on psychological and neuroscientific perspectives on animal behavior, of how agents can optimize their actions in each environment. To use reinforcement learning successfully, agents are faced with a difficult task: they must obtain efficient representations of the environments thanks to a set of sensory data. With these sensors, the agent becomes aware of its environment. When an agent performs an action, a new environment is created. An interpreter oversees the evaluation of how this new environment compares to the previous one. If it interprets that this new environment is less useful according to a certain set of rules assigned to it, it sends a negative stimulus/reward to the agent. The agent will perceive this action harmful in the context of the previous environment, and the link between the action and the previous environment is weakened. When the new environment is more beneficial than the previous one, according to the interpreter's rules, the interpreter sends a positive reward to the agent, and the agent correlates this task as beneficial to the previous environment [27]. Thanks to agent's action, a new environment is created, creating a cycle that the agent goes through. By this process of repeated trial and error, the agent will progressively learn to adapt to the rules of the environment.

There has been a lot of neuropsychological investigations into the neural basis of this method, trying to understand the parallel between neurobiological processes and the computational steps of reinforcement learning algorithms, both with animals (e.g., monkeys) and humans. In the first case, the research was mainly conducted to evaluate the choice behavior of these animals in conditions such as games [28], their choices for nutrient-defined rewards under different reward probabilities [29], and two-choice discrimination tasks [30]. Some research conducted with humans has asked participants to undergo functional magnetic resonance imaging while performing learning tasks (e.g., [31], [32]); while others investigated how human interaction can change the machine learning process based on the assumption that learning interaction with humans can help overcome some of the problems of reinforcement learning, such as speed and efficiency of exploration [33], [34]. The multi-agent reinforcement learning (MARL) field is swiftly growing, new algorithms each one with their own benefits are constantly being developed to address the challenges that come in this area. Reinforcement Learning algorithms were the foundation of a great deal of technical achievements in these past years for example OpenAIGym [35] and Upside-Down Reinforcement Learning [36]. Despite these achievements, algorithms have brittle convergence parameters, are hard to reproduce, are unreliable across runs, and sometimes outperformed by their supervised learning algorithms counterparts [37].

2.3 Game Mode

Our proposed platform includes multiplayer games, allowing more than one person to simultaneously influence play while each person is present in a shared physical or virtual space [38]. Thus, game modes are an important component to address the need to support social interactions [39] and to achieve the learning objectives of the SG [40]. Our solution will integrate competitive SG (i.e., a situation where the player is directly challenged by another player - human or computer opponents) whose performance in the game affects the other players' performance and collaborative SG (i.e., players collaborate to accomplish the shared task of beating an opponent) [38]. According to a systematic review, multiplayer game modes in rehabilitation training have improved game experience and performance compared to single-players modes [41]. Specifically, there is evidence that the collaborative game mode promoted greater behavioral involvement, while the competitive mode promoted more flow and challenge than the co-active mode with participants having higher cognitive and motor skills [42]. Another study found that competitive and cooperative games are associated with increased motivation, and competitive games are also associated with more exercise intensity [43]. In comparison to these recognized benefits of multi-user interaction in the motor rehabilitation of patients with ABI, its benefits in the CR domain remain little explored. One exception is a randomized controlled trial that found, in a sample of 43 individuals with chronic stroke, that participants in the peer-competitive group revealed greater improvements in various cognitive abilities and greater enjoyment, compared to their non-competitive peers. However, this study did not evaluate a collaborative condition [44].

2.4 Handicapping System

In non-physical digital games, player perceived difficulty is composed of four components: a) the intrinsic skill required, b) the stress placed on players by time pressure, c) the power provided to the player, and d) the amount of experience in the game (actual player skills). These elements can help game developers understand how to challenge players and thus balance non-physical digital games [45]. Playing with an agent, whether in competition or in cooperation, is a challenge. Introducing an entity that can give thousands of carefully calculated responses per minutes destroys the balance of the game. By default, an agent will inevitably outperform patients in either a competitive or cooperative game mode. To maintain patient motivation, a handicap system needs to be implemented on the agent to balance the experience. There are two different independent approaches: 1) to help/delay the player (e.g., making the objects of interest bigger/smaller or closer/more distant, increasing/reducing the number of objects on the screen, introduce new rules, making correct answer harder to distinguish from the wrong answer) and 2) to handicap the agents (e.g., by slowing down their decision making, introducing a probabilistic aspect to their decision making that represents the degree of certainty of their decision to simulate human behavior). Creating a motivating game is crucial, and the handicapping system is responsible for keeping the players' attention, not letting them overperform and not letting them underperform, while trying to maintain a facade that simulates the behavior of a human being. A famous example of this handicapping system is that of the "Super Mario Kart" games. When a player is racing against AI-controlled opponents, the game purposely handicaps, i.e., slows down the opponents ahead of the player. Separately, the game provides players with a game mechanic to outrun their opponents, an item called the "Blue Shell" which provides a means to automatically hit the opponent ahead, thus keeping the player engaged and feeling that the game is never lost. Another example would be the dart machine where the machine simulates a second player and by calculating the players' points per throw, balances their performance to create an engaging experience [46].

3. Proposed Solution

The solution proposed is a multiplayer gaming platform, CogniChallenge, for the cognitive and psychosocial rehabilitation of people with ABI. It was designed by a multidisciplinary research team with informatic engineers and a psychologist. The games were based on the existing CogniPlus platform for cognitive training [47], with similar rehabilitative features, i.e., their games already have an automatic difficulty adjustment mechanic, so we do not need third-party supervision or control to analyze. From the Cogniplus' library of games, we selected games according to their possible adaptation to real-life scenarios (ecological validity) and social skills training (psychosocial adjustment). What differentiates CogniChallenge from existing platforms is the multiplayer component to promote social interactions beyond CR. Games can be played, in a collaborative or competitive game mode, with or against other users (e.g., patients with ABI, family, friends, caregivers) or with or against virtual characters that simulate human interaction. As pointed out by Numrich [48]: "Researchers have used agent-based models in some social-science domains because they provide a somewhat natural way of thinking about the problem". To our knowledge, this is the first gaming platform for CR with a Multi-Agent System. Three CogniPlus games were adapted according to the features proposed in our proposed platform. Each game has four game modes: 1) a competitive version against an agent, in which the player competes against the agent to see who can win first; 2) a cooperative version with an agent, in which both player and agent play for a common goal; 3) a 2-player competitive version, in which two players compete to see who finishes the game first, and 4) a 2-player cooperative version, in which players cooperate to finish the level (Figure 1). Although our most important feature is the Multi-Agent System that simulates social interaction, the 2-player version is also important as it encourages social interaction and communication with other players. Each game mode is composed of three different sub-levels, totaling 29 levels. Given the importance of game clarity in games with agents, we implemented visual and sound cues for players to understand what is happening in the game. The developed games use the mouse and keyboard as the peripherals of choice to interact with the player.

Figure 1. CogniChallenge's game mode selection.

3.1 Approach

For the development of each game, the following procedure was used: a) develop the game mechanics and environment; b) develop the Multi-Agent System for each of the game modes; c) modify the Multi-Agent System for each of the 3 sub-levels of a game-mode; d) train the competitive and cooperative agents; e) handicap the agents' performance; and f) develop the 2-player cooperative and competitive versions of the game. The game engine chosen for this project was Unity, given the large amount of documentation available and the integration with the largest Reinforcement Learning Toolkit, the Unity Machine Learning Toolkit (ML-Agents). ML-Agents is an open-source project that allows the Unity engine to serve as a basis for training agent systems. Unity allows to create an environment for the agents, define the agent's sensors, and set the game rules, while the Ml-Agents toolkit is responsible for commanding the agents and their learning process. ML-Agents is composed of five main components. The first component, Learning Environment, is the Unity scenario where all the game characters (agents, players, and interactable objects) are placed. The second component, the Python-Level API, contains a low-level Python interface for interacting and manipulating the Learning Environment. Since the Python-Level API is external to the Unity Engine, a third component, the External Communicator, is needed so the Learning environment and the Python-Level API can communicate. Python trainers are the fourth component and contain all the ML algorithms that allow us to train agents. The fifth and last component is the Gym Wrapper (provided by the OpenAI Gym) [49], which allows programmers to design and compare different reinforcement learning algorithms. The Leaning Environment contains two important Unity Components: Agents and the Behaviors. Agents perform actions they receive, make observations, and assign rewards according to the results of their actions when appropriate. Each agent must have a Behavior associated with it. These receive observations and rewards from the agent and return the corresponding action to him. The behaviors can be divided into three types: Learning, Inference, and Heuristics. The Learning behavior means that the agent it's currently being trained by the Python Trainer. The Inference Behavior is an already trained Behavior that uses only a neural network file. The Heuristic Behavior governs itself according to a set of rules coded by us, if necessary. We mainly used the Learning Behavior, occasionally using the Inference Behavior to help train the cooperative agents to cooperate with already trained agents. Heuristic behavior was ultimately never used, since all decisions made by the agents come exclusively from their learned behavior. It is also important to note that while multiple agents may use the same behavior, they can still operate uniquely with each other. Having the same behavior just means that they will act according to the same set of rules, but each of these agents will perform their own observations and rewards.

The development of the SG followed the universal ethical principles of the Association of Computing Machinery [50], for example: 1) respect privacy by not monitoring the user's actions or information, and not relying on obtaining information from third-party programs; 2) honor confidentiality by never asking for the user's personal information, and 3) contribute to society and human well-being by developing a tool for cognitive and psychosocial rehabilitation.

3.2 Solution Architecture

This platform was designed with the Unity Engine to serve as a learning environment, using C as the main programming language. Next, Unity and the ML-Agents Toolkit communicate with a Python API and this API along with a yaml configuration file that contains the learning parameters of this agent. With these parameters, the Unity engine and the PyTorch reinforcement learning algorithms continue to communicate with each other via the Python API until the agent learning process stagnates or reaches a limit of iterations. This iterative process is represented in the Figure 2.

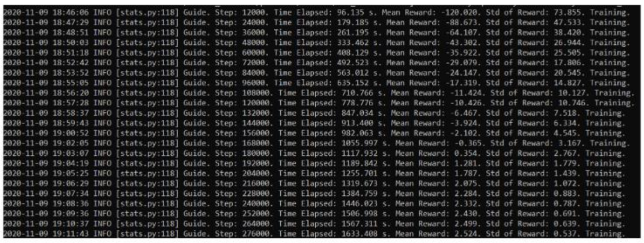

Figure 2. Agents' training process.

Throughout this process the average reward is steadily increasing, which represents that the agent is indeed learning correctly how to play the game in question. After some time, the agent's performance almost stagnates, and it is in this state that we can say that the agent has potentially learned how to play this game. In the end, a Neural Network (an.nn file) is generated which is the model of the agent. This model is then used in Unity as the "brain" of the said agent. This whole process is represented in the Figure 3. If, at the end of this process, the agent's performance does not match what is expected, it is necessary to change the reward system or adjust the reward values, restarting the whole process.

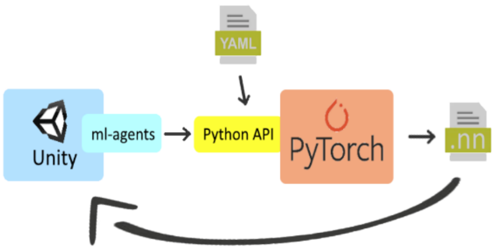

Figure 3. Visual representation of the System.

Going deeper into the structure of the yaml file, in this file we can manipulate the learning process of this agent. Figure 4 shows the yaml configuration file for the medium sub-level of the game "Route". We can select the training algorithm we want to use between PPO, SAC, and GAIL, we ended up using only PPO on all agents as it allowed a faster learning process. We have the hyperparameters, which must be adjusted for each one of the agents to have an optimal learning performance and range from the maximum number of steps used to learn, to the buffer size, to the relevance of the latest steps compared to the previous ones. Next, we have the network settings, which dictate the structure of the neural network that is generate at the end of the learning process. We had the possibility of using an intrinsic reward system (used when curiosity is implemented in the agent) or an extrinsic reward system (interaction with an environment). We used an extrinsic reward system in all agents, and with it we can define the relevance of thinking about how the current action will benefit in the long run.

```yaml
behaviors:
  Guide:
    trainer_type: ppo
    hyperparameters:
      batch_size: 64
      buffer_size: 12000
      learning_rate: 0.0003
      beta: 0.001
      epsilon: 0.2
      lambd: 0.99
      num_epoch: 3
      learning_rate_schedule: linear
    network_settings:
      normalize: true
      hidden_units: 128
      num_layers: 2
      vis_encode_type: simple
    reward_signals:
      extrinsic:
        gamma: 0.99
        strength: 1.0
    keep_checkpoints: 5
    max_steps: 5000000
    time_horizon: 1000
    summary_freq: 12000
    threaded: true
```

Figure 4. Route medium sub-level yaml configuration file.

3.3 Developed Games

The games adapted from the CogniPlus' platform were: 1) PLAND – Executive Functions: Planning and Action Skills [51], 2) NAMES – Long-term memory: Learning of face-name associations [52], and 3) CODING – Working Memory: Spatial Coding [53]. We adapted these three games to insert an agent and create a competitive/cooperative experience. The games have up to four versions, and each of these four versions has up to three different levels to make players feel like they are progressing through the game. Each of these sub-levels have a new aspect of game balance.

3.3.1 Route

It is based on CogniPlus' PLAND game [51] and the player leaves home and navigates the streets to complete his/her daily routine by visiting a set of locations. It is up to the player to find the most efficient path to visit a set of randomly generated locations in the order of his/her choosing. This game is about the player's ability to plan and execute of a set of actions with a set of daily tasks that need to be completed. The agent will be represented as another car that will compete or cooperate with the player, depending on the selected game mode. To handicap the agent, we adjusted the following parameters: the timing of each move, how quickly the agent balances its movement according to the players' movement, the randomness of the timing of these movements, and the precision of the agents' movement. There are three sub-levels, and as the player progresses though them, more destinations will be required for the player to visit, and more streets are added to the game. In the competitive game mode, the player competes with the agent to see who can visit all the required destinations first. In addition to the normal balance of the agent, the greater the win differential between the player and the agent, the faster the agent is willing act. On the other hand, if this differential is negative, the agent will act slowly. The agent is rewarded positively when it arrives at an unvisited destination. Conversely, for each move he makes without reaching a new destination, he receives a slight negative reward. An extra negative is reward is given if the agent turns back and has not reached any destination during that move. To move to the next level, the player will have to win a best-of-five match (get three wins in five games) against the agent. The only differences in the game mechanics of the levels are the size of the map, the number of locations to visit, and the number of locations in total.

The two-player version of this game mode plays is identical, the only difference is in the user interface. Since this is local cooperation, the two players share the same screen, so changes to the user interface are mandatory since the two players will end up visiting different destinations. Figure 5 shows the adapted user interface, indicating which player as visited which locations. Destinations visited by the red car have a red label, destinations visited by the blue car have a blue label, destinations with no label were not visited by either player, or, if both players visited the destinations, they disappear from the user interface. It was important to try to keep this user interface as similar as possible to the user interface of the other game mode and to adapt it to be as intuitive and natural as possible. In the cooperative version of this game, the agent cooperates with the player so that both can visit the destinations as quickly as possible. The agent checks which destinations are left to visit and the players' location. Using this information, and through the Breath First Search algorithm, the agent checks which destinations are closest to itself and which destinations are closest to the player. The agent, like the competitive version, receives a small negative reward when he moves and an additional negative reward when he retreats without any objective. However, he only receives a positive reward when he visits the locations, he is closer to compared to the player. If the agent and the player visit all locations before the time limit, they will move on to the next level. The two-player version of this game mode looks and plays the same, so no new rules have been added.

Figure 5. Sub-levels of the "Route" game.

3.3.2 Friends' names

This game is based on the game NAMES [52]. The player finds his/her friends coming to his/her birthday party and must remember their names, because later a picture of a friend's face appears, and he/she must associate it with the correct name of the friends. The game allows patients to create their own strategies to associate previously learned names with an individual. In this game, the agent is a friend of the player that greets the friends who arrive at the party. The agent gives visual cues in a textbox that represents his speech to simulate someone real. To assign a handicap to the agent, the following parameters can be changed: the time until the agents make a guess and the accuracy of that guess. There are three sub-levels, characterized by the number of friends coming to the party. For the player to move to the next level, he will have to win a best of five against the agent. The 3 sub-levels of the competitive version of this game are represented on Figure 6.

Figure 6. Sub-levels of the Friends' names game.

In the competitive version, the agent will ask the player the name of one of the friends and the player must guess correctly before the agent does. To balance the game according to the player's performance, depending on the win differential, we manipulate so that only guests of one gender show up if the player is performing well, or we ensure that the amount of guest per gender that arrive is similar in case of a poor performance. The logic being that memorizing people without this important differentiation factor will change the player's performance. The agent is rewarded positively when he guesses correctly and negatively when he guesses incorrectly. The two-player version works with the same rules, requiring only changes in the interface. Since both players need to play locally and this game requires the use of a mouse, we changed the game to be controlled on the keyboard. One player makes a guess using the number on the number pad and the other player make a guess using the keyboard (Figure 7).

Figure 7. Friends' names 2 players competitive game mode user interface.

In the cooperative version of the game, instead of guests arriving at the party individually, they will come as couples, always a woman and a man. It is up to the players to develop their own strategy to help them memorize as many faces and names as possible. The agent makes his guesses even as the player is pondering his answers. Although the answers are not guaranteed to be correct, if the agent guesses the name of the first guest correctly, it will try to guess the name of the second guest, but the chances of guessing correctly a second time are very reduced. Since the agent is no longer competing, the loss condition has been changed to a timer. Both guesses must be correct before timer runs out. To balance the game, we can additionally manipulate the accuracy of the agent's second guess. The two-player version works with the same rules. Figure 8 shows the first sub-level of this game mode.

Figure 8. Friends' names 2 players cooperative game mode user interface.

3.3.3 Traffic

It is based on CODING [53]. The player sees a series of cars on multi-lane highway and must memorize the formation of these cars and reproduce it. This game was slightly modified from the original source to implement the agent system. In the original version, instead of replicating the cars, the player had to find the car that was out of place, but this did not allow the agent to adapt its performance to that of the player, so we decided to take this new approach that still focused on the same scenario that allowed us to insert an agent. Although the player's objective is different, the process to successfully achieve it remains the same: memorize the board. This new game element makes it a little more difficult for the player to get a correct answer, because the CogniPlus game returns a nearly correct pattern to the player, giving him/her confirmations about his/her memorized guesses. Since this game does not give that information to the user, the default difficulty must be reduced. There are three different levels of the competitive version: the highway increases in size, both in length and width, and for each new level, a new car color is introduced (Figure 9). To handicap the agent, we can manipulate the following criteria: the time it takes to guess and the accuracy of that guess.

Figure 9. Sub-levels of the Traffic game.

In the competitive version, the player and the agent compete by replicating the car formation, and the one who finishes it first wins. To advance through the levels, the player will have to win a best-of-five against the agent. Both the player and the agent will have a set number of lives shared between them. To balance the game, we can manipulate the following criteria: the number of cars needed to be memorized, the speed with which the agent guesses the position, the accuracy of this/her guesses, and the number of lives. The agent is rewarded positively when he gets the answer right, and negatively when he gets it wrong. To move to the next level, the player must win a best-of-five against the agent. Since this game uses the mouse as the peripheral interface, some changes in the interface are necessary to adapt it to a 2-player version. The option would be to use the keyboard, but that would require assigning 40 different keys for both players, with each key corresponding to a point on the highway, or to use player-controlled cursors to select points on the highway. These controls would not be intuitive. For this reason, a competitive two-player version of this game was not developed.

In the cooperative version, the same set of rules applies as in the competitive version, except that the player and the agent will be guessing together, with a shared number of lives. To move to the next level, both will have to cooperate to give a correct answer before the time limit. In addition to the normal agent balancing, some balancing has been done in the rules of the game to keep the player engaged. The greater the win differential between the player and the agent, the more cars will appear to be memorized. On the other hand, if this differential is low, the number of cars required to be memorized is reduced. The speed at which cars appear on the screen during the memorization phase can also be manipulated. The agent is rewarded positively when he gets the right answer and negatively when he gets the answer wrong. If the agent is not sure that his answer is correct, he makes a random of refrains from guessing to let the player finish. In the two-player version, the car formation will only have cars of two colors. Each color is assigned to one of the players to be memorized. At the end of the memorization phase, both players must cooperate to replicate the formation, since their lives are shared, but they will take turns. First, Player 1 introduces the blue car locations, followed by Player 2 who introduces the red car locations, before the time limit.

4. Conclusions

The main objective of this proposed platform was to address the critical need for social interactions and the practice of interpersonal skills among individuals with ABI, which is often neglected in existing CR solutions. To this end, we proposed a methodology for cognitive and psychosocial rehabilitation, through the development of multiplayer SG featuring with competitive and cooperative game modes. Our gaming platform, CogniChallenge, allows individuals with ABI to play the games with other people, such as family members, caregivers, other people in the rehabilitation process, and virtual agents simulating human interaction. CogniChallenge incorporates three games based on activities of daily life, enhancing the ecological validity of the therapy. Additionally, we implemented a multi-agent game balancing system to ensure balanced gameplay and challenges, promoting sustained motivation and engagement throughout the rehabilitation process. The platform is designed to be accessible using conventional input devices such as mouse and keyboard.

Our future work involves conducting a comprehensive study to evaluate the usability and gameplay experience of the CogniChallenge SG among healthcare professionals (e.g., neuropsychologists, neurologists) and individuals with ABI. By identifying suggestions and understanding user preferences, we aim to inform the next phase of design and development with the inclusion of user preferences into the platform.

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Conflicts of interest

There are no conflicts of interest.

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