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Serious Games for Cognitive and Psychosocial Rehabilitation

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Abstract

Rehabilitation can be defined as a process designed in response to unplanned life changes imposed by illnesses or traumatic accidents. Cognitive rehabilitation is a form of therapy, focused on restoring functions that remain partially intact, applied to people with some type of cognitive impairment, such as memory loss. The problem with traditional treatment approaches is the lack of motivation and lack of interest from patients in performing repetitive tasks. Followed by this is the concept of serious games, whose main objective is not only entertainment but also educating the players.

A serious game is a game designed for a primary purpose other than pure entertainment, normally used for education, scientific exploration, health care, emergency management, city planning, engineering and/or political purpose(s). For this document, we shall focus solely on the health care purpose. Serious games are growing ever more popular due to their high engagement rate, not found on "traditional" games.

For this dissertation, a platform containing several mini-games for patients on rehabilitation of an Acquired Brain Injury was developed. As a way to keep them engaged, we'll develop agents that adjust their performance according to the patient's actions. In addition, the platform will have competitive and cooperative characteristics in order to develop patient's social skills.

The result we aim for is to develop a non-intrusive rehabilitation method, with a higher engagement rate that would relieve the health care system, while aiming to develop the patient's social, collaborative and competitive skills.

Keywords: Machine Learning, Human-Computer Interaction, Serious Games

Areas:

- CCS -> Applied computing-> Education -> Interactive Learning Environments bullet
- CCS -> Social and professional topics -> User Characteristics -> People with disabilities
- CCS-> Computing Methodologies >Machine Learning -> Learning Paradigms -> Reinforcement Learning -> Multi-Agent Reinforcement Learning

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“No man becomes rich without himself enriching others.’

Andrew Carnegie

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Abbreviations and Symbols

A2C	Advantage Actor Critic
ABI	Acquired Brain Injury
ACER	Actor Critic with Experience Relay
ASD	Autism Spectrum Disorder
EV	Ecological Validity
GE	Game Engine
IMI	Intrinsic Motivation Inventory
MAS	Multi-Agent Systems
ML	Machine Learning
ML-Agents	Unity Machine Learning Agents
NN	Neural Network
PPO	Proximal Policy Optimization
RL	Reinforcement Learning
SG	Serious Games
TBI	Traumatic Brain Injury
TT	Traditional Treatment
SAC	Soft Actor Critic

Chapter 1

Introduction

In this section we will introduce subject addressed in this project. Before we delve into an explanation of the problem matter and propose a solution, we will give some context behind the origins of this project. Afterwards are the goals that we set for a successful implementation. This section ends with an overview of the structure of the document, highlighting key-points of each chapter.

1.1 Context

Acquired Brain Injuries (ABI) are the leading cause of long-term cognitive disablility, often involving deficits in executive functions. Due to the high cost of the therapy sessions and the mobility requirements to access treatment, patients might decide to abandon treatment [4]. Serious Games (SG) present themselves as a valuable alternative since they allow patients to build problem-solving skills and critical thinking while engaging them in an interactive experience.

This project was developed for the CoRe Initiative. CoRe "Serious Games for Cognitive and Psychosocial Rehabilitation" intends to develop a new concept of cognitive and psychosocial rehabilitation based on the use of SG with social, collaborative and competitive characteristics, with the use of a multi-agent system to simulate real-life interaction on a learning environment. This system allows patients to choose from a list of mini-games against an Artificial Intelligence (AI) opponent, and adapt the opponent's performance according to the patient's stage of cognitive rehabilitation so the experience's interest is able to captivate the patient throughout the rehabilitation process.

This project will be developed with the consortium of FEUP (Faculdade de Engenharia da Universidade do Porto) and LIACC (Laboratório de Inteligência Artificial e Ciências da Computação). LIACC was founded in 1988 and aims to produce both software algorithms and prototype systems backed by relevant publications, while also assisting young researchers in developing their theses.

1.2 Objectives

The objective of this Dissertation is to provide an engaging cognitive rehabilitation alternative for ABI patients optimized for developing their social capabilities by tackling into collaboration and competitiveness. This will be done by developing a platform of games designed specifically to tackle certain areas of cognition. To reach this ambition a set of specific goals, were defined:

- Study and identification of the set of cognitive areas we want to tackle and which games on the market already tackle them;
- Study on natural interfaces to make the experience as natural as possible;
- Study and identification of the social aspect of each game, how the player can interact with the agents;
- Study and identification of handicapping systems, setting parameters to be tuned to tamper agents' performance;
- Testing the games.

The expected result is for this project to showcase the potential of use of social aspects on serious games on the motivation of the players, proving, that interaction with another patient or with an agent simulating another patient, either be it on competitive or cooperative manner, resulting in improvements on the rehabilitation process, therefore improvements on the patient's life. In case this games are being played by a singular player, they will emulate social interaction with an agent. This agents will learn by themselves how to play the game, and are balanced through the use of the handicapping system to simulate another player.

We hope that by completing these objectives and that with a confirmation from positive results, besides resulting in a positive change on patient's life, it will also result in the popularization of social interaction simulation and handicapping on the area of Cognitive Rehabilitation and Serious Games.

1.3 Dissertation Structure

This document is divided into 6 chapters: Introduction, Literature Review, Proposed Solution, Project Development, Tests and Conclusion.

Chapter 1 (Introduction) serves as a brief summary for this project, giving context, explaining the motivation and the rest of the document's structure.

Chapter 2 (Literature Review) presents an explanation on the state of the art of Acquired Brain Injuries, Cognitive Rehabilitation, Serious Games, Reinforcement Learning, Game Engines , Multi-Agent Systems and Handicapping Systems. It also showcases related projects on the market with a similar scope.

Chapter 3 (Proposed Solution) is a description of the proposed solution and how it was developed, justifying the use of the tools used, ethical concerns and the development risk that came from this decisions.

Chapter 4 (Project Development) consists on an in-depth analysis into the project and each of it's games and their development.

In Chapter 5 (Tests) we explain about our testing metric of our quiz, results of the usability test and observations that were made during these tests.

Chapter 6 (Conclusion) concludes this document, summarizing it with a brief reflexion of all the work done, and future work that could be done.

Chapter 2

Literature Review

In order to understand what makes this project unique, first an explanation is needed for Acquired Brain Injuries, Cognitive Rehabilitation, Serious Games, Multi-Agent systems, Reinforcement Learning and Game Engines followed by an analysis of similar projects currently being utilized. At the foundation of any investigation, first the problem has to be identified in order to develop an adequate solution tailored for this issue. We will explain why conventional cognitive rehabilitation methods get repetitive, turning rehabilitation into an unmotivating experience for the patients which translates into inefficient results, and how games can help us on this subject-matter.

2.1 Acquired Brain Injury

An ABI is an injury to the brain that is non-degenerative, non-congenital, non-hereditary and it's not induced by birth trauma. These kinds of injuries occur after birth and result in a change of the brain's neuronal activity, affecting physical integrity, metabolic activity, or functional ability of nerve cells in the patient's brain. ABI are divided into two categories: Traumatic Brain Injury (TBI): caused by the head forcibly hitting an object, or an object piercing the skull (e.g. falls, motor accidents, assaults) and Non-Traumatic (NTBI): caused by internal forces (e.g. strokes, near-drowning, aneurysm, tumor, heart attack) [5].

The complexity of the brain and its responsibility for all aspects of human development and activity means that the effects of an ABI are widespread, and no two people with an acquired brain injury will be affected in the same way. These injuries may cause serious physical, cognitive and psychosocial deficits and increase the risk of developing neurodegenerative diseases [6].

Cognitive deficits are a common expression of highly prevalent neurological and psychiatric conditions that may affect individuals of all ages. Neurological disorders are diseases that affect the brain and the central and autonomic nervous systems. There are many types of neurological disorders, including: Alzheimer's disease, Multiple sclerosis, Parkinson's disease, epilepsy, etc. Cognitive training plays an important role in the treatment of patients with cognitive deficits [7].

TBI's, by themselves, are a prevalent cause of death and disability with over 3.8 million annual cases and 130 daily deaths in the United States alone [8]. TBI remains a growing public health concern and represents the greatest contributor to death and disability global among all trauma-related injuries [9]. In 2019, the United States of America estimated that 2.8 million people sustained a TBI, from which 282,000 were hospitalized and 56,800 died [10] . These numbers don't include NTBI's which are rising as the average life expectancy grows.

In Europe 2015, for all ages and TBI severities, crude incidence rates ranged from 47.3 per 100,000, to 694 per 100,000 population per year. Crude mortality rates ranged from 9 to 28.10 per 100,000 population per year [11].

In Portugal, the incidence rate decreased, being 137/100 000 in 1997 and 65/100 000 in 2014. The mortality rate has also decreased from 17/100 000 to 10/100 000. However, between 2011 and 2014, there was a trend to increase the total number of cases. The incidence rate by age group also differed, with fewer cases in the young adult population in 2014 contrasting with a very high mortality among people aged 80 or older, of 57/100 000 [12].

Once a person has survived an ABI, there's a plethora of side-effects that will affect his/her life. These are divided into 3 categories: physical (muscle dis-coordination, full/partial paralysis, changes in senses, headaches), cognitive (memory loss, difficulty in learning new concepts, poor critical thinking) and emotional/behavioral (depression, easily frustrated, regression with social skills) [13].

2.1.1 Cognitive Rehabilitation

Brain Injuries often lead to residual impairments that persist well beyond the hospital level of care. These residual impairments lead to physical, cognitive, emotional and behavioral symptoms. For the scope of this project, we shall focus on the cognitive aspects.

Cognitive impairments are a major factor of loss of autonomy and dependence, and, consequently, reduce the patient's quality of life. Cognitive rehabilitation is mandatory so that patients can recover as much capabilities as possible and return to their everyday lives.

Cognitive rehabilitation is defined as a process whereby people with brain injury work together with health professionals and others to remediate or alleviate cognitive deficits arising from a neurological insult [14]. Cognitive Rehabilitation typically requires participants to complete a set of repetitive exercises the patient responds to visual or audio stimulus. For example, Sohlberg and Mateer [15] created an Attention Process Training program, one of it's simpler tasks required patients to press a buzzer whenever they heard the number 3. The tasks progressively got harder. In another more difficult task that was used, months of the year were shown one at a time, the participants must press the buzzer whenever the currently presented month is the same month that immediately preceded the previously presented month. There is an abundant variety of cognitive rehabilitation programs, it's up for a professional to analyze a patient case by case. Occupational therapy is well-suited for addressing the cognitive deficits experienced by individuals with an ABI, since it helps regain or maintain the skills needed to an healthy daily life [16].

Cognition refers to the mental processes that are involved in acquiring knowledge and comprehension, that is, the capabilities or intellectual skills that make us think, perceive things, acquire, understand, and respond to information. These include the abilities to: pay attention, remember, work information, solve problems, organize and reorganize information, communicate and to act upon information. All of these capabilities work in their own and connect with one another to allow us to function in our environment.

Cognitive rehabilitation involves an evaluation of the individual's general intellectual functioning. Tests of intellectual function examine the performance of diverse mental functions (e.g. attention, memory, processing speed, visual-spatial perception and construction, verbal comprehension). For each of these mental functions, there is a variety of measures used by clinicians to help their patients namely the *Hopkins Verbal Learning Test and California Verbal Learning Test* for memory training and the *Conner's Continuous Performance Test and Symbol DigitModalities Test* for attention assessment [17]. After these tests is up to a professional so select a rehabilitation strategy and to see how the patient reacts to it. Since there is a lot o variability on the patient's response to these strategies, it's preferable to try several strategies as a means to determine what works best for each patient [18]. These methods of rehabilitation will be considered, from now on, as Traditional Treatment (TT).

Rehabilitation can be divided into two phases: the acute phase and the chronic phase. The acute stage occurs between 0 to 6 months after the patient's incident. In this stage, most of the improvements occur, especially physical improvements since these manifest earlier than cognitive improvements. In the chronic/post-hospital phase, the impact of the residual impairments on the patient is felt on his/her everyday life. This dissertation focuses on this second stage.

This type of extensive care is provided by post-hospital comprehensive rehabilitation programs. Patients have specialized rehabilitation programs designed for them which involve one or more of the following aspects: physical therapy, physical medicine, occupational therapy, psychiatric care, psychological care, speak and language therapy and social support. This program can take place in various settings: Inpatient rehabilitation hospital, Outpatient rehabilitation hospital, Home-based rehab, an independent rehabilitating center and a Comprehensive day program [19].

Despite all of these efforts, how long the patient will be on rehabilitation and how much follow-up they will need afterwards depends on the severity of the injury and on how well the patient responded to therapy. Some patients might keep their previous abilities intact while others might need life-time care in order to maintain the ones they currently have.

2.2 Games

On this section we will be discussing the current state of the art when it comes the Serious Games industry, the Multi-Agent Systems, Multi-Agent Learning, Game Engines and well established Systems for Cognitive Rehabilitation already on the market.

2.2.1 Serious Games

The term "Serious Game" was coined by Clark Abtan in his 1970 book "Serious Games" [20], in order to differentiate games for fun and games for learning. In this book, he referred to the use

Figure 2.1: Serious Game oriented towards Alzheimer patients

of physical games, namely board and card games. Although he did not refer to SG as computer games, he proposed a definition that is still applicable even in today's computer age:

> "Reduced to its formal essence, a game is an activity among two or more independent decision-makers seeking to achieve their objectives in some limiting context."

The "Serious Game" term, as we today acknowledge it, was first used in 2002, with the creation of the Serious Game Initiative lead by David Rejeski and Ben Sawyer in the United States of America.

SG can be applied to a broad spectrum of application areas like military, government, educational, corporate, healthcare and so on, they can come in any genre. SG are conceived to train people for tasks in particular jobs. More recently, serious games are being developed to tackle a range of behavioural and attitudinal issues. The term SG is used in reference to any kind of game for learning where the games are designed with the intention of improving some specific aspect of learning that is relevant, instantly useful, and fun [21]. SG are a relatively new area of research and combine the interactivity and entertainment of games with a serious purpose in order to develop a specific set of skills. For example, on Figure 2.1, is a SG designed to evaluate Alzheimer patients cognitive status through the use of six daily life task composed by three navigation tasks: one shopping task, one cooking task and one table preparation task, following a one-day scenario. To note how this task simulates our daily life tasks, this way it ensures that the knowledge gained from this task is related to the knowledge the patient would gain in his daily life routine, also know as Ecological Validity [22].

On the last few years of SG's happened on the mobile market, there's a lot of mobile games oriented towards brain training and cognitive stimulation whose objective is not just to entertain the player to kill some time (although that is the starting point) but to stimulate thoughts, logic, memory, etc. SG's don't have a concrete definition, but for the rest of this dissertation we will consider them to be computer games whose main purpose is to stimulate the player's cognition with the help of the entertaining nature of video-games.

SG's are not strictly better than Traditional Treatments, but the qualitative comparison made between them leads us to think that SG are more powerful than TT in improving safety training in a variety of technical aspects. The following table 2.1 compares these two methods according to the research made by Gao et al. [23]. Several studies on cognitive rehabilitation state that the effectiveness of the treatments when the patients are doing intensive tasks with a set goal that can be divided in several repetitive sub-tasks ([24], [25]). However the repetitive nature of these sub-tasks is one unmotivating aspect about these treatments, and if the patient is not motivated to perform well in the games, the rehabilitation process won't be as efficient as desired. Professionals in the rehabilitation state that patient's motivation plays a mandatory role in the rehabilitation process ([26], [27]). Motivated patients understand that playing a more active role in therapy is their fastest route to an healthy rehabilitation, so they strive to maintain a positive attitude throughout the entirety of the procedure. J. Hamari and J. Tuunanen concluded [28], that the five key dimensions in which a game can motivate the players are: Achievement, Exploration, Sociability, Domination, and Immersion. There's also the Intensity dimension, but this dimension can either motivate or unmotivate the players, some players prefer harder experiences and others might prefer casual experiences.

Table 2.1: Strengths and weaknesses of SG and TT, adapted from Gao et al.

Approach	Strengths	Weaknesses
SG	Simulate actual workplace dynamics. Text-free Graphical Interfaces. Higher knowledge retention. Engagement and Interactivity. Stimulate situational awareness. Multi-collaboration. Egocentric interface. Reward system and storyline. Data reliability. Risk-free and accessible at home. Alternative Challenges levels.	Computer skills required. Complex 3D navigation. Less effective for skillfull patients.
TT	Suitable for unskilled computer users. Hands-on practice allows interaction. Easy-carrying educational materials.	Inapplicable for on-site situations. Difficult for communication impaired patients. Less engagement. Unsatisfied knowledge retention.

2.2.2 Multi-Agent Systems

Multi-Agent Systems(MAS) have been studied as a field since 1980 and the field gained mass recognition in the mid 1990s. Since then, interest has kept growing because of the belief that agents are an appropriate software paradigm through which to exploit the possibilities presented by massive open distributed systems like the internet or even real life examples like stock market [29], healthcare [30] or even board games [31] . MAS seem to be a natural metaphor for understanding and building a wide range of what we might crudely call artificial social systems [32].

MAS are systems composed of multiple independent interacting computing elements, known as Agents. Agents are entities focused on achieving a certain goal through observing the environment around them and making an action. Agents are computer systems capable of autonomous action, depending on how their behaviours and interactions with the environment are set. Agents are even capable of interacting with other agents or players — not simply by exchanging data, but by engaging in simulations social activities that we all engage in our everyday life.

In the last few years, the interest to commercialize this technology has risen. The interest MAS is largely founded on the insight that many real world problems are best modelled using a set of agents instead of a single agent. The reason agents are such an important aspect, is that they simulate the learning behaviours. They possess the ability to learn and adapt their behaviour which is one of the most important features of intelligence through the use of positive and negative reinforcement [33].These agents can gives us answers to maximization problems and be used as simulations. One controversial example was done by the Facebook AI Research team, and they created two agents that managed to negotiate items with one another while learning english from scratch with one another [34]. Examples like these arise ethical concerns brought with the use of this technology.

A recent study [35] states that there is no need of urgency for addressing societal concerns. Ethics is one such concern but it is closely related to other 4 societal concerns: Fairness, Accountability, Transparency and Privacy .

- *Fairness* - Relates to the judgements on the outcomes of the predictions done by the agents. Each agent must understand contextually relevant-norms for the subject they are being used upon and reasoning of value preferences of the stakeholders around it, not just itself;
- *Accountability* - actions need to be traceable and sanctioned when appropriate;
- *Transparency* - Relates as well to the principle of traceability, agent's reasoning should be explicable in run-time;
- *Privacy* - Comprises the concerns such as confidentiality and avoiding infringing into others' space. The flow of private user's information violates contextual norms.

This study laid a foundation for what a system like this should abide from now on.

When designing MAS, it is impossible to foretell all the potential situations an agent may face and develop an agent's behaviour optimally in advance, specially because when an agent is interacting with another agent the possibilities rise exponentially. Agents therefore have to learn from, and adapt to, their environment, especially in a multi-agent setting. This is where Multi-Agent Learning is utilised to integrate Machine Learning Techniques into a Multi-Agent System to create these adaptive agents. The most popular Multi-Agent Learning technique, and the one that we used during this project is Reinforcement Learning.

2.2.3 Reinforcement Learning

Reinforcement learning provides a normative account, based in psychological and neuroscientific perspectives on animal behaviour, of how agents may optimize their actions on a given environment. To use reinforcement learning successfully, agents are confronted with a difficult task: they must obtain efficient representations of the environments thanks to a group sensory inputs. As an example, an agent simulating a human would have 5 sensors: sight, hearing, touch, smell and taste. With these sensors it will perceive the environment around him.

When an agent performs an action a new enviroment is created. An interpreter is in charge of evaluating how this new environment compares to the previous one. If it interprets that this new environment is less usefull according to a certain rule-set it was given, he sends a negative stimulus/reward to the agent. The agent will perceived this action as harmfull on the context of the previous environment, and the link between the action and the previous environment is weakened. When the new environment is considered to be more beneficial than the previous one according to the Interpreter's rule-set, it sends a positive reward to the agent, and the agent will correlate this task as beneficial to the previous environment.

With this information, by generalizing past experiences (associating the environment, the performed action and how valuable the outcome was), and applying and comparing these to new situations [36]. Thanks to the action of the agent, a new environment is created, creating a cycle that the agent iterates through. This process is visually represented on the Figure 2.2. Through this process of repeated trial and error the agent will steadily learn how to adapt to the rules of the environment.

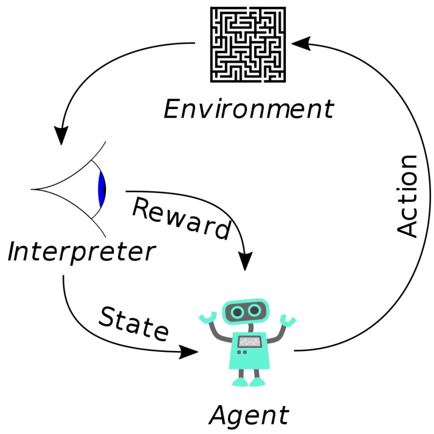


Figure 2.2: Reinforcement Learning cycle

There's a lot of neuropsychological investigations into the neural basis of this method. For example Britten [37] and Shadlen and Newsome [38] experiences on monkeys. By showing a kinometograms of random dots, some dots move coherently with one another in a given direction, and some moving erratically. It's the monkey's job to determine in which direction the coherent dots are moving in just from watching a 2 second clip. The coherence level of this dots could be manually manipulated, and by the end of the experiment the monkeys had an almost perfect performance up until when the kinometograms only has from 10% to 15% of coherent dots.

The multi-agent reinforcement learning (MARL) field is swiftly growing, new algorithms each one with their own benefits are constantly being developed these last years 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 [39] and Upside Down Reinforcement Learning [40].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 [41].We will now describe some of this algorithms.

2.2.3.1 Advantage Actor Critic (A2C)

Multi-agent reinforcement learning systems overcome the issue of scalabity that come in having multiple agents by distributing the global control with each agent. This presents new problems since the environment now is partially observed by each agent, since the communication between these is limited. Advantage Actor Critic also known as A2C comes as an alternative to the other Reinforcement Learning algorithms presenting itself as a decentralized and fully scalable multi-agent machine learning algorithm [42]. If need be for agents to act on parallel to their surroundings a similar algorithm should be used, the Asynchronous Advantage Actor Critic (A3C).

2.2.3.2 Actor Critic with Experience Replay (ACER)

ACER [43] is an off-policy implementation of A3C. Off-Policy means that when the agent is in it's learning process, when he is faced with a situation, instead of just considering the action he is going take, it considers all the actions done in this specific situation, by using an experience relay buffer to record actions,states and rewards during the training process.

2.2.3.3 Proximity Policy Optimization (PPO)

PPO [3] focus on solving the brittle convergence parameters, while giving developers a simpler approach, that is easier to reproduce that is applicable on a more general setting with an overall improvement in performance, especially on how fast these algorithms can train new agents.

PPO was tested on the Atari benchmark tests against the implementations of two other alrotigthms: A2C and ACER. During this tests the algorithms are tuned to play 49 Atari games. To measure the algorithm's performance were used two scoring metrics: average episode reward over all of training, and average episode reward over the last 100 episodes. Average episode reward over all of training evaluates how fast this algorithm is able to learn, and the average episode reward over the last 100 episodes evaluates which algorithm ended up with the best performing agent. The results are displayed on Table 2.2.

Table 2.2: Results of the Atari benchmark test, from John Schulman [3]

	A2C	ACER	PPO	Tie
Average episode reward over all of training	1	18	30	0
Average episode reward over the last 100 episodes	1	28	19	1

2.2.3.4 Soft Actor Critic (SAC)

SAC [44] is an off-policy maximum entropy reinforcement learning algorithm that provides sample-efficient while retaining the benefits of entropy maximization and stabilization. SAC considers that the most valid action on a said environment is the action with the biggest entropy, meaning the action with the biggest average reward.

2.2.4 Social Aspects

Some games might force player to interact with one another competitively or cooperatively directly, but some games might tackle the social aspect in indirect ways, for example platforms like Lumosity [45] with the use of leader boards where you can see the player's high-scores. Some applications take it even farther and allow players to share the results online, so be it through private messages or social media. During competition scenarios, players will have difference levels of cognitive disparities, since the objective is not to make a purely competitive game but an engaging game a balance system has to be implemented either benefiting the more handicapped player or impair the less handicapped player, or somewhere between these two options options. Another social aspects of social interaction comes in an indirect manner as related on [46]. Games can be as a means to start a conversation and further connections with the people surrounding the player. In the article is given the example of a grandmother talked to her grandson about playing games. This let's the family and friends take in an active role in the rehabilitation process.

Three out of four patients described spending a lot of time alone [46], since they might need to be left alone in their houses or in the hands of a caretaker. Serious Games that provide a sense of social connection may help decrease this sense of loneliness and this sense of connection is easy to tackle when the family and friends takes an active part in helping the patient.

2.2.4.1 Cooperation

By using cooperative characteristics in games, promotes interaction between player. Both players need to communicate, evaluate each other feedback and reach an hopefully common conclusion. Both players motivate each other to finish the tasks demanded of them.

In a rehabilitation context, a research was made with two boys with Autism Spectrum Disorder(ASD) [1]. The boys had similar severy of ASD and similar side-effects, inclusively social deficits. They were forced to cooperate to complete 2 puzzles. Both boys overtime begin esbilishing comunication and some simple cooperation methods, starting from separating both of their pieces, to both of sending sending feedback to one another. This research is shown on the Figure 2.3.

Cooperation serves as social support tool for the patient with the people arround him, namely family, friends and other patients. These support serves as the start of conversations and story telling and as motivation for the patients to finish the exercises, resulting in better results at end.

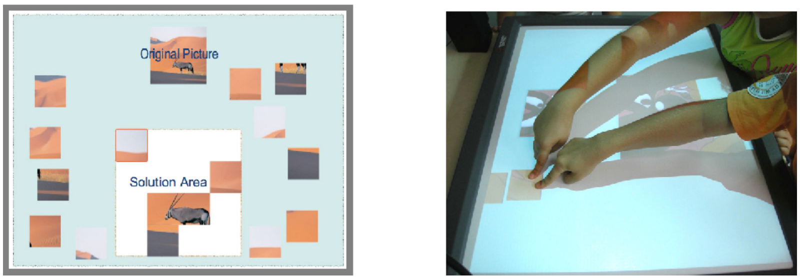


Figure 2.3: Two boys with ASD cooperating to complete a puzzle from [1]

2.2.4.2 Competition

Through the usage of competitive characteristics in a game, it is pretended to appeal to the competitive side of the players. Both players motivate each other until completing determined tasks. Normally to make this fair, games implement a system called Skill Based Match Making [47], which basically is a skill rating associated to each player represent how good he is at said game. This skill rating is inferred from previous game sessions.

When bringing competitive aspects into cognitive rehabilitation, ideally two patients with the same degree of cognitive dissonance should be competing, but this isn't always possible due to the variety of cognitive deficits that Acquired Brain Injuries cause. Using Skill Based Match making could be an option, but patient's performance might vary tremendously from game to game depending on which kind of deficits he/she manifests, requiring the use of multiple skill ratings. Skill ratings take time to adjust to the correct value because it's a process of inference, during this process the patient will be facing uneven matches against other patients. To solve this issue some games create a simulated player. This simulated player performance can be tuned accordingly to the player by professionals, or even done automatically during the game session, this process of adjusting the performance of a simulated player/agent is called Handicapping System.

2.2.5 Handicapping System

In digital, non-physical games, the player perception of difficulty is composed of four components: the intrinsic skill required, the stress placed on the players by time pressure, the power provided to the player and the amount of in-game experience (actual player skills). These elements can help game designers to understand how to challenge the players and thus balance digital non-physical games [48].

Playing with an agent, be it competitively or cooperatively presents a challenge. Introducing an entity that can make thousands of carefully calculated answer per minutes destroys the game balance. An agent by default will unavoidably outperform the patients either one a competitive gamemode or on a cooperative gamemode, so in order to retain the patient's motivation, a handicap system needs to be implemented within the agent to balance the experience, there are two different independent approaches. The first approach is to help/slow the player (e.g. making objects of interest bigger/small or closer/further, increase/reduce the amount of objects on screen, introduce new rules, make correct answer harder to distinguish from the wrong answer). The second option is to handicapp the agents (e.g. slowing down their decision-making, introduce a probabilistic aspect into their decision-making representing how certain they would be of their decision to simulate human behaviour). Making a motivating game is crucial, and the handicapping system is in charge of keeping players in their toes, not letting them over-perform and not letting them under-perform, while trying to maintain a facade simulating the behaviour of a human being . One famous example of this handicapping system is on the "Super Mario Kart" games. When a player is racing against AI controlled opponents, the game purposely handicaps the speed of the opponents in front of the player. Separately, the game provides the players with game mechanics to overtake his/hers opponents, an item named "Blue Shell" that provides a mean to automatically target and guarantee an hit in the opponent in the lead, thus keeping the player engaged and feeling that the game is never lost. Another example would be the dart machine developed by Battocchi [49], the machine simulates a second player, and by calculating the average points per throw of the player it balances it's performance to create and engaging experience.

2.2.6 Game Engines

There's an ever growing landscape of Game Engines (GE). For the purpose of this dissertation we will only take in consideration free GE that are available to the general public since some GE were built from scratch by specific companies and their code isn't available to the general public (e.g. Frostbite). Moreover, Game Engines which strongest features are oriented toward visual effects (e.g. CryEngine) aren't relevant to the scope of this dissertation, since, in order to take advantage of said features, a team of modellers and artists is needed. GE' s that don't have MacOS support are neglecting 17,99% of possible devices [50], so they won't be taken into consideration. The three most know GE that fit this criteria are Unity, Unreal Engine and Godot.

Before comparing the GE themselves, first we will compare their market presence. In order to beat the agent, we ran a script designed by [51] that obtains the name of all the games present in Steam (the biggest online-gaming platform), and with these names, we then searched on Wikipedia if there's any information regarding the corresponding GE. In case there is not, it will be registered as "Unknown". Figure 2.4 represents the result of this script. Unity corresponds to 11%, Unreal Engine to 23% and Godot has a residual presence, about 0%. These numbers don't directly correspond to Game Engine's popularity in general since AAA games (games distributed by major publishers) tend to have extra downloadable content and, for this script, these count as new games, improving Unity and mainly Unreal Engine presence on this platform.

On a technical aspect, Unity is a free-to-use beginner friendly GE, but its engine and executables tend to occupy more hard drive space than its competitors. On a financial aspect, despite being free, if the game revenue surpasses 100 thousand dollars annually, Unity requests us to buy a Unity Pro subscription (150$ per year). Unity also doesn't provide grants to its developers.

Unreal Engine is a very powerful GE oriented towards experienced users and designed for development of AAA games. It provides its users with a plethora of available tools, and excels on rendering technology. Recently it's licensing terms have changed, and Unreal is now free-to-use

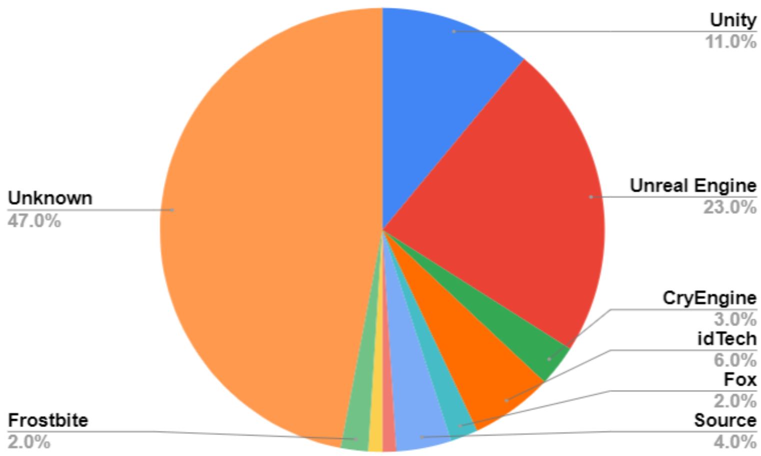


Figure 2.4: Game Engines popularity according to Steam

until a game's lifetime gross revenue exceeds one million dollars. It this case we'll have to pay 5% on royalties.

Godot is an open-source flexible GE, where the developed project belongs solely to it's developers, meaning no fees will be applied. However, it is lacking on features compared with the two previous options, and, since it's community is quite small, there's an evident lack on documentation [52].

2.2.7 Systems for Cognitive Rehabilitation

In order to understand what makes this project unique, we shall first review the most popular and already established Serious Games Platforms on the market. These are *RehaCom*, *NeuronUp*, *CogniPlus*, *Cognifit* and *Luminosity*. After some research we decided to discard *Luminosity* due to some studies questioning its Ecological Validity, and *Luminosity* was instructed to deliver refunds. Since the other four are established and proven successful game platforms, they will be further analysed in this section. On the following table, we analyzed these platforms to verify which has the most similarities to this project.

2.2.7.1 RehaCom

The RehaCom clinical tool, as seen in Figure 2.5, consists of 29 minigames/modules that automatically adapt the difficulty according to the patient's performance. Therapists and Patients create their profiles and the patient is assigned to multiple therapists. Therapists can then prescribe modules for their patients to do, monitor progress and change their tasks using remote supervision. The therapist is able to change module parameters such as the duration of session, the starting level of the session, how sensitive the adaptability should be, time limit to solve tasks, audio feedback, stimuli sources and more. RehaCom uses its own custom controller, specifically designed for ease-of-use. It is designed to train Attention, Memory, Executive Function, Visual Field and VisuoMotor abilities [53].

Figure 2.5: Rehacom tool

Table 2.3: Already established Serious Games platforms

Products	RehaCom	NeuronUp	CogniPlus	Cognifit
Cognitive Dimensions	Attention Memory Executive Functions Visual Field VisuoMotor Skills	Memory Attention Gnosis Executive Functions Social Cognition Visuospatial Skills	Concentration Memory Executive Functions Memory Attention Driving	Executive Functions Reasoning Concentration Driving Coordination Memory Visuospatial Skills
Benefits	Flexibility Accessibility Scientifically Validated	Large Selection Scientifically Validated Real-life context exercises	Driving Related Abilities Automatically adapts difficulty	Scientifically Validated Large Selection
Limitations	Need of a professional	Need of a professional		

2.2.7.2 NeuronUP

NeuronUP, as seen in Figure 2.6, is a web platform designed to act as a support for professionals involved in cognitive rehabilitation and stimulation processes. Patients can schedule with several types of professionals in the area (speech therapists, occupational therapists, etc). It consists of numerous materials and resources for designing treatment sessions in addition to a patient manager for organizing and saving the results of those sessions [54]. These sessions' activities are based on everyday life and designed to stimulate memory, attention, *gnosis*, executive functions, *praxis*, language, executive functions, social cognition and visuospatial skills.

2.2.7.3 CogniPlus

CogniPlus, as seen in Figure 2.7, is a computerized cognitive training program aimed at improving general cognition, in particular attention to working memory and executive functions, all

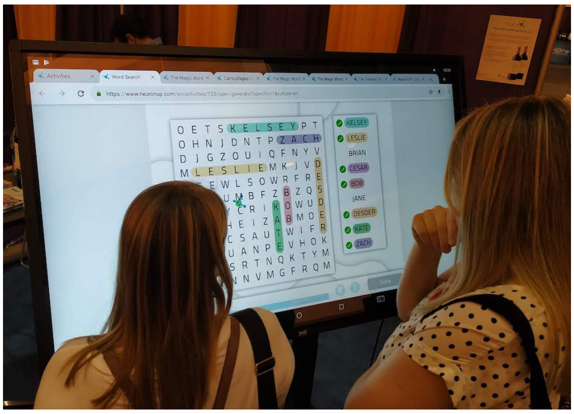


Figure 2.6: NeuronUp Tool

cognitive domains that are frequently impaired in patient that suffer from TBI [55]. CogniPlus adapts the difficulty of its exercises according to the patient by identifying his/her ability level and adapting according to it [56].

Figure 2.7: CogniPlus tool

2.2.7.4 CogniFit

CogniFit, seen in Figure 2.8, is a global leader in developing online programs that focus core cognitive areas like attention, memory, coordination, perception and reasoning with the use of validated cognitive tests and brain training programs. The patient plays a set of mini-games, and their performance is stored to be analyzed by a professional, comparing it to previous playthroughs to check concrete cognitive deficits or alterations [57].

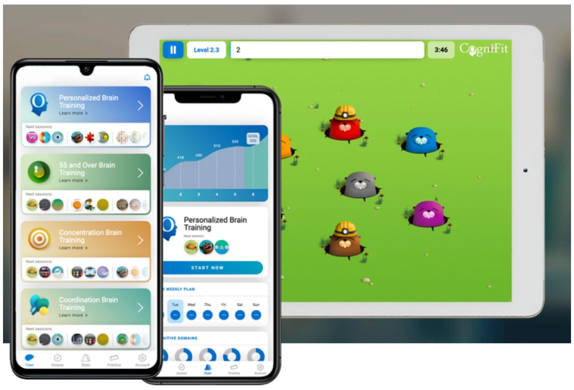


Figure 2.8: CogniFit tool

Chapter 3

Problem and Proposed Solution

3.1 Problem

Professionals on ABI rehabilitation state that effective treatment is on a short supply [58]. Every year, 15 million people worldwide suffer a stroke. Acquired brain trauma is the second most prevalent disability in the U.S. [59]. Statistical data show that after a stroke, one-third of patients die during the first month, and 40% of people who recover from the acute phase exhibit a high degree of impairment that decreases their independence and quality of life. Only one-third of patients recover their basic functions and can resume a normal life [60].

Two thirds of all people with an ABI who have their activity limited or restricted are over the age of 45. One third of those are over the age of 65. The largest age group is between 40 and 49 [61].

People suffering from impairments may not be able to go to an hospital by themselves, or might even need to stay under surveillance on the hospital. Besides the patient occupying space for another potential patient, this patient will cost to the hospital around $38018 a year in Toronto's case [62].

3.2 Solution

Our proposed solution is a game platform, CogniChallenge, composed of games that will help patients in rehabilitation of acquired brain injuries. What differentiates CogniChallenge from those previously mentioned is the simulated multiplayer component. As Numrich [63] said:

> "Researchers have used agent-based models in some social-science domains because they provide a somewhat natural way of thinking about the problem".

The objective isn't just to improve the patient's cognitive status: it's to improve his/hers psychosocial state as well. The players play against agents in mini-games that simulate daily life activities, whose difficulty is tailored according to the patient's performance in order to stimulate him/her and simulate human interaction. This point is crucial and is our unique selling point, since

Figure 3.1: CogniChallenge's game mode selection menu

if the player is not engaged to try to improve while performing repetitive tasks, the rehabilitation will not be effective. To our knowledge, no other project has implemented a Multi-Agent System like this. Unlike NeuronUp where they can adapt the difficulty and adaptability manually, the objective is for this to be done automatically, similar to CogniPlus.

Each game has four game modes: a competitive version against an agent where the player is competing against the agent to see who can successfully complete the winning condition first, a cooperative version with an agent where both the player and the agent play for a common goal, a competitive 2 player version where two player compete to see who finishes the game first successfully, and a cooperative 2 player version where players cooperate to finish the level 3.1. Despite our selling point being the Multi-Agent System simulating social interaction, 2 player version are also valuable since they stimulate social interaction and communication with other players. Each game mode is composed of three different sub-levels that the player will proceed through as a reward for a good performance to motivate the players through achievement, but as the player proceeds through these sub-levels new game mechanics are introduced to keep players engaged and to manipulate further their performance. The mini-games were developed with the supervision of LIACC.

3.3 Approach

In order to facilitate the development of this project, we defined a plan. Throughout the development of the project, three games were developed, these are composed in a total of 29 levels. These games resemble daily life scenarios and tasks to ensure as high as possible ecological validity degree. This way, the lessons the patient is learning are as relevant as possible to his/hers daily life.

In order to develop each game, the following procedure was used: develop the game mechanics and the environment, develop the Multi-Agent System for each of the game mode, modify the h]

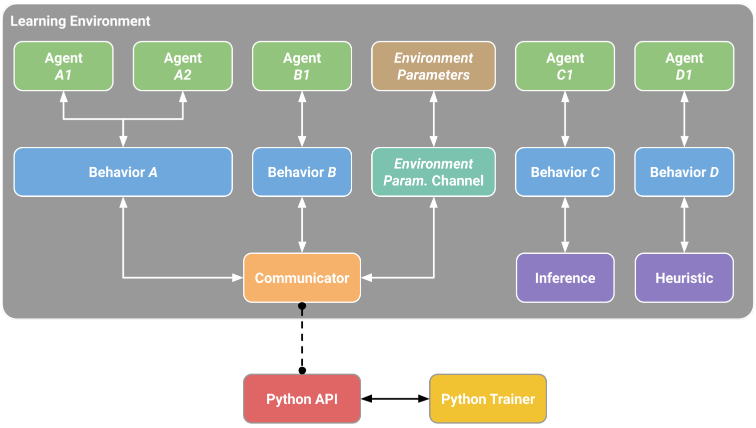


Figure 3.2: A learning environment using ML-Agents and the Unity Editor, adapted from Juliani et al. [2]

Multi-Agent System for each of the 3 sub-levels of a game-mode, train the competitive and cooperative agents, handicap the agents' performance, develop the 2 player cooperative and competitive versions of the game.

The GE chosen for this project was Unity. Although Unreal Engine is a very powerful tool, and has a lot of documentation available, we didn't find it to match the scope of the project since Unreal is normally used for AAA games. Unity is free to use, only requiring a monthly fee if said game profits more than 100 thousand dollars per year. Despite this, it has plethora of documentation available as well as integration with the biggest Reinforcement Learning Toolkit, Unity Machine Learning Toolkit (ML-Agents).

ML-Agents is an open-source project that allows the Unity Engine to serve as a basis to train Agent Systems. Unity allows you to create an environment to the agents upon, to define the agent's sensors and to define the game rules, while the Ml-Agents toolkit is in charge of commanding the agents and their learning process. ML-Agents is composed by five key components. The first component, Learning Environment, is the Unity scene where all the game characters (agents, players and interactible objects) are placed in. 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 required so the Learning environment and the Python-Level API can communicate. The Python trainers are the fourth component and contain all the ML algorithms that allow us to train agents. The fifth and final component is the Gym Wrapper (provided by the OpenAI Gym [64]), which allows the developers to design and compare different reinforcement learning algorithms.

The Leaning Environment contains two important Unity Components: the Agents and the Behaviours. The Agents perform the actions they receive, make observations and assign rewards according to the results of their actions when appropriate. Every agent must have a Behaviour associated with it. These receive observations and rewards from the agent and returns him the according action. The behaviours can be divided into three types: Learning, Inference and Heuristic. The Learning behaviour signifies that the agents it's currently being trained by the Python Trainer. The Inference Behaviour is an already trained Behaviour that uses only a neural network file. The Heuristic Behaviour rules itself according to a set of hard-coded rules set by us if needed. We mainly used the Learning Behaviour, occasionally using the Inference Behaviour to help train the cooperative agents cooperate with already trained agents. The Heuristic behaviour ended up never being used since, all the decisions made from the agents come uniquely from their learnt behaviour. It's also important to note that even though multiple agents might use the same behaviour, they can still operate uniquely to one another. Having the same behaviour only means that they will perform according to same rule-set, but each of these agents will perform its own observations and rewards.

3.4 Chosen platform

Implementing rehabilitation characteristics into games is a challenging task that should be done and evaluated with a multidisciplinary team of specialists in their own respective areas of expertise. Because of this concern, while developing this platform, we wanted to guarantee that the developed games are backed up with some sort of validity in our claims of it's rehabilitation value.

Between the four stated systems on the previous section: RehaCom, NeuronUp, Cogniplus and Cognifit, we chose CogniPlus to base this project upon. Despite having games simulating real-life scenarios, similar to our desired end product, the difficulty in NeuronUP is the manually adjusted by the professionals creating said therapy sessions. The games are not designed from the ground-up to have an adjustable difficulty scaling. While RehaCom and Cognifit are game-platforms designed with several games (some applied on real-life scenarios), with multiple difficulty levels and tunable parameters, these need to be set manually through a professional that analyzes player performance. In contrast, CogniPlus is a cognitive training program with difficulty levels that automatically adjust its' exercises to the patient's performance, making CogniPlus the rehabilitation system closer to CogniChallenge's goal. Since most of Cognifit's games are not set on real-life scenarios, these games will be adjusted visually, while maintaining the game-mechanics intact in order to maintain Ecological Validity.

3.5 Ethical concerns

It is our duty to develop this project accordingly to the universal ethical principals across the development phase and the testing phase. The Association of Computing Machinery instated a Code of Ethics [65] to guide and inspire all computing professionals and practitioners. To be noted several topics:

- *Respect privacy* - we, at no point, monitor the user's action or information, and CogniChallenge doesn't rely on getting information on 3rd party programs;
- *Honor confidentiality* - we never ask for the user's personal information, besides at the usability test, and even on this case the user's anonymity and confidentiality is guaranteed.
- *Contribute to society and to human well-being, acknowledging that all people are stakeholders in computing* - this is the critical key-point, we need to guarantee that CogniChallenge benefits the society, we guarantee this by building our platform according to an already established and scientifically proven platform (CogniPlus).

The MAS will not be making any judgments or actions that were not premeditated by the developers. We can guarantee that this system will abide to the previously explained study [35] four corner pillars concerns.

3.6 Development Risks

Although games might have simple concepts, these evolve overtime, forcing potentially major game-play mechanics which consequently forces changes and a new training on all related agents. Besides the technical changes, in order to create a compelling game there's a lot of criteria that needs to be met: balancing fun factor and learning factor, figuring out the desired learning outcomes.

Since each game has up to 4 game modes, each one up to three different levels, each minigame has have six different agents, each one needing to be individually balanced and trained. New training sessions and new balancing are required with new code iterations. An agent performance can only be evaluated after training. Inconclusive debugging due to the impossibility of replicating bugs due to the uncertainty of the environment and of the agents actions in a controlled fashion.

Even if an agent is successfully trained, it will need to be handicapped to balance its performance while inserting some randomness at the same time to imitate human behaviour, otherwise we will be left with an inflexible handicap system, this comes full circle with the last issue, making it more inconclusive trying to debug the agents' behaviours.

Ml-Agents toolkit does not maintain documentation for it's past versions of it's software. It also forces the use of an outdated Unity engine version. Optionally if the agents can be trained in a faster fashion with the GPU instead of the CPU, which was the case, creates the need to install outdated versions of TensorFlow, Cuda Toolkit and cuDNN SDK.

Chapter 4

Project Development: CogniChallenge

4.1 Solution Architecture

Throughout this project a game platform was developed focused on cognitive rehabilitation and social interaction. All of the assets found in this project are copyright free and were slightly modified, or made from scratch. All the sounds, music and the images of the people on the second mini-game (Nomes) are copyright-free, all other resources are original or modified specifically for this project.

4.2 Implemented Characteristics

We chose the Cogniplus games platform [66] to serve as a guideline since it's games already have an automatic difficulty adjustment mechanic, so we do not need supervision or 3rd-party control to analyze, thus fitting the scope of this dissertation's objective.

We analyzed Cogniplus' games library and decided which games we could adapt to train social competences and add a real-life scenario which requires the same effort from the player, while trying to focus on as many cognitive functions domains as possible. The social aspect will be implemented by forcing the player to interact with another player, or with an agent, either cooperating or competing against them.

One extremely important aspect that needs to be emphasized when playing against an agent is the game clarity. Since if the player is having a good performance, the speed of the game can turn chaotic, in order for the players to understand what is currently happening on the game, mainly the agent's actions, visual and audio cues were implemented to the mini-games.

The developed games use both the mouse and the keyboard as the peripherals of choice to interface with the player.

4.3 Implementation

The developed serious games function directly through an executable file created thanks to the Unity Engine, therefore the main programming language used was C#.

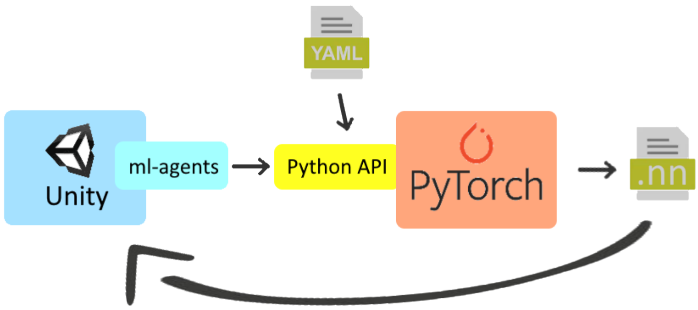


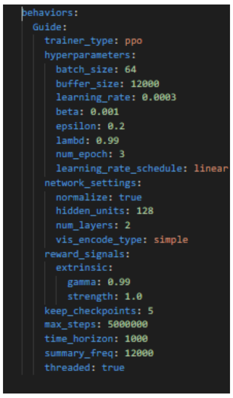
Figure 4.1: Visual Representation of the System

This platform was designed with the Unity Engine to serve as a learning environment, using C as the main programming language. Then Unity and the ML-Agents Toolkit communicate with a Python API and this API together with an yaml configuration file containing the learning parameters of this agent. With these parameters, the Unity engine and the PyTorch reinforcement learning algorithms keep communicating with each other through the Python API until the agent's learning process has stagnated or reached a limit of iterations. This iterative process is represented on the Figure 4.2. To note that, throughout this whole process the mean reward is steadily increasing, representing that the agent is indeed learning correctly how to play the game in question. After some time, the agent performance nearly stagnates, it's at this state that we can say that the agent has potentially learnt how to play this game. At 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 said agent. This whole process is represented in the Figure 4.1. If by the end of this process, the agent performance doesn't act has expected, either changing the reward system or tuning the rewards values is needed, and we restart this whole procedure.

```
2020-11-09 18:46:06 INFO [stats.py:118] Guide. Step: 12000. Time Elapsed: 96.135 s. Mean Reward: -120.020. Std of Reward: 73.855. Training.
2020-11-09 18:47:29 INFO [stats.py:118] Guide. Step: 24000. Time Elapsed: 179.185 s. Mean Reward: -88.673. Std of Reward: 47.533. Training.
2020-11-09 18:48:51 INFO [stats.py:118] Guide. Step: 36000. Time Elapsed: 261.195 s. Mean Reward: -64.107. Std of Reward: 38.420. Training.
2020-11-09 18:50:03 INFO [stats.py:118] Guide. Step: 48000. Time Elapsed: 333.462 s. Mean Reward: -43.302. Std of Reward: 26.944. Training.
2020-11-09 18:51:18 INFO [stats.py:118] Guide. Step: 60000. Time Elapsed: 408.129 s. Mean Reward: -35.922. Std of Reward: 25.505. Training.
2020-11-09 18:52:42 INFO [stats.py:118] Guide. Step: 72000. Time Elapsed: 492.523 s. Mean Reward: -29.079. Std of Reward: 17.806. Training.
2020-11-09 18:53:52 INFO [stats.py:118] Guide. Step: 84000. Time Elapsed: 563.012 s. Mean Reward: -24.147. Std of Reward: 20.545. Training.
2020-11-09 18:55:05 INFO [stats.py:118] Guide. Step: 96000. Time Elapsed: 635.152 s. Mean Reward: -17.319. Std of Reward: 14.827. Training.
2020-11-09 18:56:20 INFO [stats.py:118] Guide. Step: 108000. Time Elapsed: 710.766 s. Mean Reward: -11.424. Std of Reward: 10.127. Training.
2020-11-09 18:57:28 INFO [stats.py:118] Guide. Step: 120000. Time Elapsed: 778.776 s. Mean Reward: -10.426. Std of Reward: 10.746. Training.
2020-11-09 18:58:37 INFO [stats.py:118] Guide. Step: 132000. Time Elapsed: 847.034 s. Mean Reward: -6.467. Std of Reward: 7.518. Training.
2020-11-09 18:59:43 INFO [stats.py:118] Guide. Step: 144000. Time Elapsed: 913.400 s. Mean Reward: -3.924. Std of Reward: 6.334. Training.
2020-11-09 19:00:52 INFO [stats.py:118] Guide. Step: 156000. Time Elapsed: 982.063 s. Mean Reward: -2.102. Std of Reward: 4.545. Training.
2020-11-09 19:02:05 INFO [stats.py:118] Guide. Step: 168000. Time Elapsed: 1055.997 s. Mean Reward: -0.365. Std of Reward: 3.167. Training.
2020-11-09 19:03:07 INFO [stats.py:118] Guide. Step: 180000. Time Elapsed: 1117.932 s. Mean Reward: 0.354. Std of Reward: 2.767. Training.
2020-11-09 19:04:19 INFO [stats.py:118] Guide. Step: 192000. Time Elapsed: 1189.842 s. Mean Reward: 1.281. Std of Reward: 1.779. Training.
2020-11-09 19:05:25 INFO [stats.py:118] Guide. Step: 204000. Time Elapsed: 1255.701 s. Mean Reward: 1.787. Std of Reward: 1.439. Training.
2020-11-09 19:06:29 INFO [stats.py:118] Guide. Step: 216000. Time Elapsed: 1319.673 s. Mean Reward: 2.075. Std of Reward: 1.072. Training.
2020-11-09 19:07:34 INFO [stats.py:118] Guide. Step: 228000. Time Elapsed: 1384.759 s. Mean Reward: 2.284. Std of Reward: 0.883. Training.
2020-11-09 19:08:36 INFO [stats.py:118] Guide. Step: 240000. Time Elapsed: 1446.023 s. Mean Reward: 2.332. Std of Reward: 0.787. Training.
2020-11-09 19:09:36 INFO [stats.py:118] Guide. Step: 252000. Time Elapsed: 1506.998 s. Mean Reward: 2.430. Std of Reward: 0.691. Training.
2020-11-09 19:10:37 INFO [stats.py:118] Guide. Step: 264000. Time Elapsed: 1567.311 s. Mean Reward: 2.499. Std of Reward: 0.639. Training.
2020-11-09 19:11:43 INFO [stats.py:118] Guide. Step: 276000. Time Elapsed: 1633.408 s. Mean Reward: 2.524. Std of Reward: 0.537. Training.
```

Figure 4.2: Agent's training process

Going in-depth on the structure of the yaml file, in this file we can manipulate this agent's learning process. On the Figure 4.3 is shown the yaml configuration file for the medium sub-level of the game "Percurso". We can select which training algorithm we want to use from PPO, SAC and GAIL,we ended up only using PPO on all the agents since it allowed for a faster learning process. We have the hyperparameters, these need to be tuned for each one of the agents to have an optimal learning performance and they range from the max number of steps used to learn, to buffer size, to how relevant the latest steps compared to previous steps are. Next we have network settings, which dictates the structure of the neural network that is generate at the end of the learning process. On we can use either an intrinsic reward system (used when curiosity is implemented on the agent) or an extrinsic reward system (interaction with an environment). We used an extrinsic reward system on all of the agents, and with it we can define how relevant thinking how the current action will benefit down the line is.



```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 4.3: "Percurso" Medium sub-level yaml configuration file

4.4 Developed Games

The games we decided to adapt were PLAND [67], NAMES [68] and CODING [69] (visually represented on Figure 4.4, represent by image 1, image2 and image 3 respectively), focusing on memory, learning, attention, decision making and planning.These games were already inspired on real-life scenarios, so we ended up just adapting the games to insert an agent to make a competitive/cooperative experience. The games will have up to four versions: a competitive version against an agent, a cooperative version against an agent, a competitive two player game mode and a cooperative two player game mode. Each of these four versions will have up to three different levels in order for the players to feel like they are progressing throughout their playthrough. Each of these sub-levels have a new gameplay balance aspect. For the rest of this section we will delve in more detail for each game in the following section.

Figure 4.4: CogniPlus' games that were adapted

4.4.1 Percurso

Our first game "Percurso" (based on PLAND, represented on Figure 4.4 with the number 1), works the planing and decision making capabilities on the player. The player will get out of their house and navigate through the streets in order to complete his/hers daily life routine, by visiting a set of locations. It's up to the player to find the most efficient route to visit a set of randomly generated locations, in any order he/she so wishes to. In this game is tackled the player's planning capabilities and the execution of a set of actions through the use of a set of daily tasks that need to be completed.

The agent in this game will be represented as another car that is going to be either competing or cooperating with the player depending on the selected game-mode. To handicap the agent, we can tweak the following parameters: time of each play; how fast the agent balances its time of movement according to the players movement, how random the time of these moves can be and how accurate an agent move is. There are three sub-levels and, as the the player progresses though them, the more destinations will be required for the player to visit and more streets are added to the game.

4.4.1.1 Competitive Version

On the competitive game-mode, the player will be competing with the agent, to know who is able to visit all of the required destinations first. Besides the normal balancing of the agent, the bigger the win differential between the player and the agent, the faster the agent is gonna act. On the other hand, if this differential is negative the agent will act slower. The agent is rewarded positively when it reaches an unvisited destination. On contrast for every move that he makes

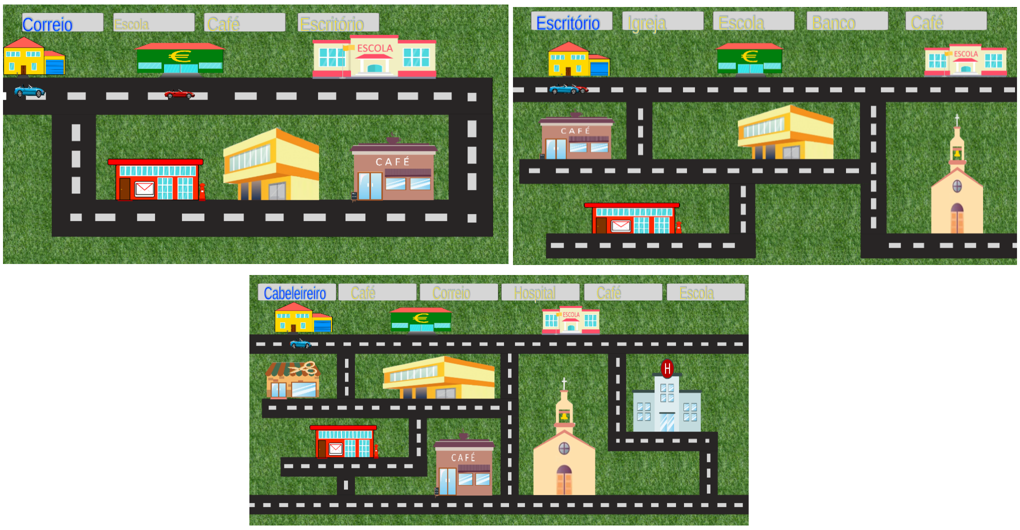


Figure 4.5: 3 Sub-levels of the "Percurso" game

where no new destination is reached, he gets a slight negative reward. An extra negative is reward is given if the agent backtracks and no destination was reached during this movement. In order to proceed to the next level, the player will have to win a best of five (get three wins in five games) against the agent. The only differences on the levels game-play mechanics are the map size, the amount of places needed to visit and the amount of places in total. The two player version of this game-mode plays exactly the same, the only difference is on the user interface. Since this is local cooperation both players share the same screen, so changes on the user interface are mandatory since both players will eventually visit different destinations. On Figure 4.6 shows the adapted user interface, showing which player as visited which locations. Destinations visited by the red card will have a red label, destinations visited by the blue car have a blue label, destinations without a label were not visited by neither player, and, if both players visited the destinations it disappears from the user interface. It was important to try to maintain this user interface as similar as possible to the other gamemode's user interface, and to adapt it to be as intuitive and natural as possible.

Figure 4.6: "Percurso" 2 players competitive gamemode user interface

4.4.1.2 Cooperative Version

On the cooperative version of this game, the agent will be cooperating with the player so that both of them can visit the destinations as fast as possible. The agent will notice what destinations are still to be visited and the location of the player. Using this information and, through Breath First

Search algorithm, the agent checks which destinations are closer to itself and which destinations are closer to the player. The agent similarly to the competitive version gets a small negative reward when moving and an additional negative reward when backtracking with no purpose. However we will only get a positive reward when visiting the locations that he is the closer to compared to the player. If the agent and the player visit all places before the time limit they will advance to the next level. The two player version of this game-mode plays and looks exactly the same, so no new rules were added.

4.4.2 Nomes

In the game "Nomes" (based on NAMES, represented on Figure 4.4 with the number 2), the player is trained to develop efficient strategies to learn and associate them to faces. The player will be meeting his/hers friends coming to his/hers birthday party. The player will need to remember each of his/hers friends names, because later on, a picture of a friend's face will show up, and they will need to associate it with the correct guest's name. The game allows patients to create their own efficient methodology to associate names previously learnt with an individual.

Figure 4.7: 3 Sub-levels of the "Nomes" game

The agent in this game is a player's friends that greets the friends arriving at the party. The agent gives visual cues on a text-box representing its speech to simulate someone real. To handicap the agent, the following parameters can be modified: the time until the agents makes a guess and how accurate this guess is. There are three sub-levels, characterized by the amount of friends coming to the party. In order for the player to proceed to the next level, they will need to win a best of five against the agent. The 3 sub-levels of the competitive version of this game are represented on 4.10.

4.4.2.1 Competitive Version

On the competitive version, the agent will ask the player for one of the friends name and the player must guess correctly before the agent does so. In order to balance the game according to player performance, depending on the wins differential, we manipulate so that it only shows guests of one gender if the player is having a good performance, or guarantee that the amount of guest per gender arriving is similar in case of a bad performance. The logic being that memorizing people without such important differentiation factor will tamper player's performance. The agent is positively rewarded when guessing correctly and negatively rewarded with an incorrect one. The two player version works with the same rule-set, only requiring interface changes. Since both players need to play game locally and this game requires the usage of the mouse, we changed the game to be controlled on the mouse to be controlled on the keyboard. One player takes a guess using the number on the numeric pad and the other player will take a guess using the keypad 4.8.

Figure 4.8: "Nomes" 2 players competitive gamemode user interface

4.4.2.2 Cooperative Version

On the cooperative version of the game, instead of guests individually arriving at the party, they will come as couples instead, always one female guest and one male guest. It's up to the players to develop their own strategy to help them memorize as many faces and names as possible. The agent will make its guesses even while the player is pondering their answers. Although responses are not guaranteed to be correct, and if the agent guesses the first guest's name correctly, they will try to guess the second guest's name, however the chances of correctly guessing a second time are greatly reduced. Since the agent is no longer competing, the losing condition was changed into a timer. Both guesses need to be correctly made before a timer runs out. In order to balance the game we can additionally manipulate the accuracy of the agent's second guess. The two-player version works exactly under the same rule-set. On the figure 4.9 is represented the first sub-level of this game mode.

Figure 4.9: "Nomes" 2 players cooperative gamemode user interface

4.4.3 Trânsito

The last game "Trânsito" (based on CODING, referencing Figure34.4 with the number 3), targets monitoring. The player will see a series of cars on an highway with multiple lanes. They will need to memorize these cars formation and replicate it. This game's objective on the player is to tackle monitoring and spacial coding processes, at the level of visual-spatial memory. This game was slightly modified from the original source in order to implement the agent system. On the original version [69], instead of replicating the cars, the player had to find the car that was out of place, but this didn't let the agent adapt its performance to the player's, so we decided to take this new approach that still focused on the same scenario and the same cognitive domain that allowed us to insert an agent, while maintaining ecological validity. Although the player's objective is different, the process to successfully achieve it is still the same: memorizing the board. This new gameplay element makes it slightly harder for the player to get a correct answer, because the CogniPlus game gives an almost correct pattern back to the player, giving the player confirmations on their memorized assumptions. Since this game doesn't give that information back to the user, the default difficulty needs to be lowered. There are three different levels for the game (represented on 4.10 the 3 levels of the competitive version): the highway increases on size, either on length or on width, and, for each new level, a new color of car is introduced. In order to handicap the agent, we can manipulate the following criteria: time it takes for them to guess and how accurate this guess is.

4.4.3.1 Competitive Version

In this version, the player and the agent will compete by replicating the car formation, and whoever finishes it first will win. In order to proceed through the levels, the player will need to win a best of five against the agent. Both the player and the agent will have a set amount of lives shared between them.

To balance the game, we can manipulate the following criteria: the number of cars needed to memorize, the velocity as which the agent guesses the position, how accurate the agent guesses are and the number of lives. The agent is positively rewarded when guessing a right answer, and

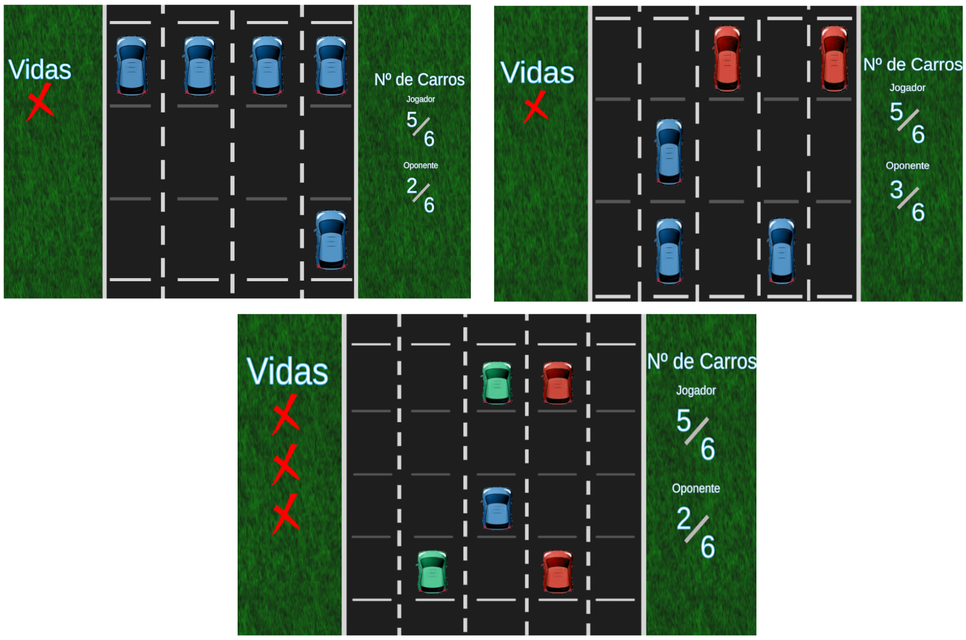


Figure 4.10: 3 Sub-levels of the "Trânsito" game

negatively rewarded on a wrong one. To progress to the next level the player will need to win a best of five against the agent. Since this game uses the mouse as the interface peripheral, it requires some interfaces changes to adapt it to a 2 player version. The option would be to use the keyboard instead but this would require to allocate 40 different keys for both players, each key corresponding to a spot on the highway, or to use cursors controlled by the players to select spots on the highway. These controls would not be intuitive. On that basis, no competitive version for two players of this game was developed.

4.4.3.2 Cooperative Version

On the cooperative version, the same rule-set of the competitive version applies, with the difference being that the player and the agent will be guessing together, with a shared amount of lives. To proceed to the next level, both will need to cooperate in order to give a correct answer before the time limit. Besides the normal balancing of the agent, some balance on the game rules was done to keep player engaged. The bigger the win differential between the player and the agent, the more cars will show up to be memorized. On the other hand, if this differential is low, the number of cars needed to be memorized is reduced. The velocity at which the cars show up on screen during the memorization step can also be manipulated. The agent is positively rewarded when guessing a right answer, and negatively rewarded on a wrong one. If the agent isn't sure if its answer is correct he will either give a random guess or restrain itself from guessing to let the player finish.

On 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 need to cooperate to replicate the formation, since their lives are shared, but they will take turns. First, Player 1 will input the blue car's locations, followed by Player 2 inputting the red car's locations, before the time limit.

Chapter 5

Testing and Results

Because of the current pandemic crisis, we are unable to test this product with patients on the process of cognitive rehabilitation. All the tests were made on individuals with no cognitive deficits, and they were all made online.

We used a according to the Intrinsic Motivation Inventory (IMI) interdimensional device intended to assess participants' subjective experience related to a target activity in laboratory experiments. These were designed to measure the usability of the platform and how enjoyable/interesting the games of our platform are [70]. Some questions about feedback, and information about the individuals themselves were also added.

5.1 Sample Characterization

On the following table (5.1) is showcased the sample of individuals that played CogniChallenge.

Seven people participated on this test, the whole sample played CogniChallenge online. From the 7 participants, 6 (85,7%) were male and 1 (14,3%) was female. The average age of the participants is 22,57 years and it ranged between 19 and 25 years. 6 (85,7%) frequented or are currently frequenting higher education. Everyone used the computer everyday. Only 1 tester (14,3%) played games regularly and the other 6 (85,7%) play video-games everyday.

5.2 Measures

IMI is a multidimensional measurement device intended to assess participants' subjective experience related to a target activity [71], in this case, their experience using the CogniChallenge platform. IMI assesses participants' Interest/Enjoyment, Perceived Competence, Effort/Importance, Value/Usefulness, Felt Pressure and Tension, and Perceived Choice while performing a given activity. To measure these factors there's a methodology to calculate 6 different sub-factors for each factor. For this Usability Test we measured the 4 factors that we found relevant for this project, for each game: Interest/Enjoyment, Perceived Competence, Effort/Importance and Pressure/Tension.

Table 5.1: Sample Characterization [3]

	Sample (N=7) n	%	Avg	SD
Age			22,57	1,82
Gender				
Masculine	6	85,7		
Feminine	1	14,3		
Level of education				
High School	1	14,29		
Masters	5	71,43		
Doctorate	1	14,29		
Video-Game Usage				
Everyday	6	85,71		
Regularly	1	14,29		

Note: Avg - Average, **SD** - Standart Deviation.

5.2.1 Results

The results of this test are on a scale of 1 to 7 and are represented on detail in 5.2, 1 standing that the player strongly disagrees with the statement and 7 that he/she strongly agrees with the statement. To note that the only factor that we are trying maximize is the Interest/Enjoyment, the other 3 are supposed be dynamical balancing themselves not having neither an high evaluation nor a low evaluation. The results of the usability tests on the games are shown on Appendix A.1.

Table 5.2: Results of the IMI usability test

Factors	**Games**			
	Percurso	**Nomes**	**Trânsito**	Average
Interest/Enjoyment	4,47	4,47	4	4,31
Perceived Competence	4,33	3,93	3,79	4,02
Effort/Importance	3,77	4,17	4,43	4,12
Pressure/Tension	2,71	3,86	3,54	3,37

In the "Percurso" game, 7 players (100%) played both the competitive and cooperative game-modes against the agent. One player (14,29%), played the competitive and cooperative 2 player version of the game. On the "Nomes" game, 7 players tested the competitive game-mode against the computer and six played the cooperative version against the agent. One player played both the competitive and the cooperative 2 player version. On the "Trânsito" game, 7 players tested the competitive game-mode against the computer and six played the cooperative version against the agent. No players played 2 player versions.

5.3 Additional Observations

On this section we shall cite observations that were made during the testing session. Since all the test were made online we couldn't observe the players themselves.

From this testing sessions, it was observed that users had difficulties in understanding the instructions from the "Trânsito". Either not knowing where to click or how to change car's colours. Everyone thought that the "Percurso" game starting levels were too easy, but in the "Nomes" and "Trânsito" they tended to be silent while playing, showing that the game captured their focus.

Most of the players were not informed of the scope and objective of these games, they just knew that they were going to be playing some game, and they manifested surprise as the agent was giving them a gradually lower margin of error, some even mentioned how it was getting faster or how they thought that the names that they were forced to memorize were getting more similar.

Chapter 6

Conclusion

This final chapter serves as a summary of this documentation and all the work done.

Although valuable and efficacious, traditional cognitive rehabilitation takes a lot of time to accompany millions of patients potentially for the rest of theirs lives. Serious Games come as an alternative to relief the burden on the Healthcare, and when speaking of interactive Serious Games, game engines presented themselves as a powerful creation tool.

The Game Engines provide tools that allows a more engaging experience alternative to Traditional Rehabilitation. Since this experience doesn't require continuous surveillance from an health professional, the need for patients to meet their consultants is reduced.

The range of results these games may have on a specific patient is very wide since this depends on the patients condition, since ABI's may cause impairments on multiple areas (physical, cognitive and psycho-social), the place of the injury, the amount of time between the incident and treatment, etc.

Coming into this project we were expecting to build not necessarily a perfect balancing system but as close to that as possible. The truth is that perfection will never be achieved, but, in order to reach the realistic goal we will need a lot of play-testing to fine tune the adjustable hyper parameters o the yaml configuration file, and the in-game variables. Besides that, testing with our target audience (patients in cognitive rehabilitation) was not possible because of the current pandemic crisis we live in.

This project was developed for the CoRe Initiative and will accompany "Jogos Sérios para Rehabilitação Cognitiva" by Rui Rocha [72]. This project is also a game's platform oriented towards patient in cognitive rehabilitate of ABI's, but instead of focusing on the simulated multiplayer component with the agents, it focus on multi-modal interfaces.

The final product of this investigation is a game-platform, composed of 3 games that can be played competitively or cooperatively, against/with an agent or against another player, divided into 29 sub-levels in total. The agent's performance adapts according to player's performance, through an handicapping system. As the player progresses through the game, new game mechanics are introduced. These game mechanics also adjust themselves to player performance. The "Percurso" game was clearly too easy for the testers, since the agent didn't act entirely as expected and players were able to somewhat beat the game without even looking at the destinations and just finding an effective route to visit every location.

These testing sample is our biggest limitation. The tests have a small sample size and they are not the target audience, so the values presented on the usability test need to be taken with a grain of salt, and in case of doubt all the difficulty and performance indicators should be taken as inflated values.

6.1 Future Work

Since the Unity Engine has multi-platform support, it can be used on another types of devices including WebGL. This enables this project to be played on web-browsers. Developing new games, especially games that tackle more areas of cognition to create a more versatile product that were not addressed just with 3 games.

Another usefull aspect would be an optional window before each game to manually define the parameters that compose the agent's handicap system.

More testing on the target market is necessary.

Regarding the difficulties on the game "Trânsito", the game was made from the ground up so that the cars can stop in the middle of the screen, just adjusting this parameter should be enough to fix this issue.

The performance of the agents of the first game, "Percurso", should be tested with the SAC algorithm, and compared with the performance with the PPO algorithm. The agent might have a potentially better performance at the end of it's learning process.

Appendix A

Usability Test Results

Table A.1: Usabily Test Results 1/4

	Avg
I liked this game.	**4,75**
Percurso	4,57
Nomes	4,86
Trânsito	4,81
This Game was fun to play.	**4,57**
Percurso	4,71
Nomes	4,71
Trânsito	4,29
This game was boring to play.	**3**
Percurso	2,86
Nomes	3,14
Trânsito	3
This game did not hold my attention at all.	**3,64**
Percurso	4,48
Nomes	3,29
Trânsito	3,14

Table A.2: Usabily Test Results 2/4

	Avg
I would describe this game as very interesting.	**4,76**
Percurso	4,43
Nomes	4,86
Trânsito	5
I thought this game was quite enjoyable.	**4,38**
Percurso	4,29
Nomes	4,43
Trânsito	4,43
While playing, I was thinking about how much I enjoyed it.	**2,95**
Percurso	3
Nomes	2,86
Trânsito	3
I think I am pretty good at this game.	**4,43**
Percurso	4,86
Nomes	4,14
Trânsito	4,29
I think I did pretty well at this game, comparatively.	**3,57**
Percurso	3,43
Nomes	3,71
Trânsito	3,57
After sometime playing this game, I felt pretty competent.	**4,05**
Percurso	4,29
Nomes	4,28
Trânsito	3,57
I am satisfied with my performance in this game.	**4,52**
Percurso	5
Nomes	4
Trânsito	4,57
I was pretty skilled at this game.	**3**
Percurso	3,29
Nomes	2,86
Trânsito	2,86

Table A.3: Usabily Test Results 3/4

	Avg
This was a game that I couldn't perform very well.	**3,48**
Percurso	2,86
Nomes	3,43
Trânsito	4,14
I put a lot of effort into this game.	**3,81**
Percurso	2,42
Nomes	4,14
Trânsito	4,86
I didn't try very hard to do well at this game.	**5,33**
Percurso	5,57
Nomes	5,14
Trânsito	5,29
I tried very hard on this game.	**5,19**
Percurso	4,86
Nomes	5,29
Trânsito	5,43
It was important to me to do well at this game.	**4,33**
Percurso	3,86
Nomes	4,71
Trânsito	4,43
I didn't put much energy into this game.	**3,66**
Percurso	4,14
Nomes	3,86
Trânsito	3
I did not feel nervous at all while playing this game.	**4,24**
Percurso	5,86
Nomes	2,71
Trânsito	4,14
I felt very tense while playing this game.	**3,10**
Percurso	2,57
Nomes	3,71
Trânsito	3

Table A.4: Usabily Test Results 3/4

	Avg
I was very relaxed in playing this game.	**3,95**
Percurso	4,57
Nomes	4
Trânsito	3,29
I was anxious while playing this game.	**2,24**
Percurso	1,71
Nomes	2,29
Trânsito	2,71
I felt pressured while playing this game.	**3,29**
Percurso	2,57
Nomes	3,86
Trânsito	3,43

Appendix B

Version of Development Tools

For this project we used Unity 2019.4.10f1, TensorFlow 2.3.0, Cuda 10.1.105,cuDNN v8.0.4, Anaconda 2020.07 and Python 3.8.3.

These software versions should be maintained since they all are interconnected with one another, the need to change one tool version will result in the likely need to change all the other tools versions.

References

[1] A. Battocchi, E. Gal, A. B. Sasson, F. Pianesi, P. Venuti, M. Zancanaro, and P. Weiss, "Collaborative puzzle game-an interface for studying collaboration and social interaction for children who are typically developed or who have autistic spectrum disorder," *7th ICDVRAT with ArtAbilitation. ICDVRAT/University of Reading, UK*, pp. 127–134, 2008.

[2] A. Juliani, V.-P. Berges, E. Vckay, Y. Gao, H. Henry, M. Mattar, and D. Lange, "Unity: A general platform for intelligent agents," *arXiv preprint arXiv:1809.02627*, 2018.

[3] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv preprint arXiv:1707.06347*, 2017.

[4] G. Shochat, S. Maoz, A. Stark-Inbar, B. Blumenfeld, D. Rand, S. Preminger, and Y. Sacher, "Motion-based virtual reality cognitive training targeting executive functions in acquired brain injury community-dwelling individuals: A feasibility and initial efficacy pilot," in *2017 International Conference on Virtual Rehabilitation (ICVR)*, pp. 1–8, 2017.

[5] "What is the difference between an acquired brain injury and a traumatic brain injury?," May 2020. https://www.biausa.org/brain-injury/about-brain-injury/nbiic/what-is-the-difference-between-an-acquired-brain-injury-and-a-traumatic-brain-injury.

[6] A. S. Vincent, T. M. Roebuck-Spencer, and A. Cernich, "Cognitive changes and dementia risk after traumatic brain injury: Implications for aging military personnel," *Alzheimer's Dementia*, vol. 10, no. 3, Supplement, pp. S174 – S187, 2014. Military Risk Supplement.

[7] P. A. C. de Sousa Rego, "Serious games for health rehabilitation," 2017.

[8] A. Balakrishnan and S. Patapati, "Automation of traumatic brain injury diagnosis through an iot-based embedded systems framework," in *2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, pp. 645–649, 2017.

[9] A. M. Rubiano, N. Carney, R. Chesnut, and J. C. Puyana, "Global neurotrauma research challenges and opportunities," *Nature*, vol. 527, no. 7578, pp. S193–S197, 2015.

[10] "Brain Injury Statistics," May 2020. https://www.knappandroberts.com/brain-injury-statistics/.

[11] B. A. V. M. V. M. M. W. V. A. L. A;, "Epidemiology of traumatic brain injury in europe: A living systematic review." https://pubmed.ncbi.nlm.nih.gov/26537996/.

[12] S. M. N;, "Traumatic brain injury in portugal: Progress in incidence and mortality." https://pubmed.ncbi.nlm.nih.gov/31442091/.

[13] P. Rego, P. M. Moreira, and L. P. Reis, “Serious games for rehabilitation: A survey and a classification towards a taxonomy,” in *5th Iberian Conference on Information Systems and Technologies*, pp. 1–6, 2010.

[14] J. Solana, C. Cáceres, A. García-Molina, E. Opisso, T. Roig, J. M. Tormos, and E. J. Gómez, “Improving brain injury cognitive rehabilitation by personalized telerehabilitation services: Guttmann neuropersonal trainer,” *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 1, pp. 124–131, 2015.

[15] M. M. Sohlberg and C. A. Mateer, “Effectiveness of an attention-training program,” *Journal of clinical and experimental neuropsychology*, vol. 9, no. 2, pp. 117–130, 1987.

[16] N. W. Park and J. L. Ingles, “Effectiveness of attention rehabilitation after an acquired brain injury: A meta-analysis.,” *Neuropsychology*, vol. 15, no. 2, p. 199, 2001.

[17] T. Tsaousides and W. A. Gordon, “Cognitive rehabilitation following traumatic brain injury: assessment to treatment,” *Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine: A Journal of Translational and Personalized Medicine*, vol. 76, no. 2, pp. 173–181, 2009.

[18] M. Kelly and M. O’Sullivan, “Strategies and techniques for cognitive rehabilitation: Manual for healthcare professionals working with individuals with cognitive impairment,” 10 2015.

[19] “Rehabilitation after traumatic brain injury,” Jun 2020. https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/rehabilitation-after-traumatic-brain-injury.

[20] C. Abt, “Serious games. e viking press,” *New York City, New York, USA, st edition*, 1970.

[21] A. L. Brooks and E. Brooks, “An internet of things resource for rehabilitation,” in *2014 International Conference on Collaboration Technologies and Systems (CTS)*, pp. 461–467, 2014.

[22] N. Chaytor and M. Schmitter-Edgecombe, “The ecological validity of neuropsychological tests: A review of the literature on everyday cognitive skills,” *Neuropsychology review*, vol. 13, no. 4, pp. 181–197, 2003.

[23] Y. Gao, V. A. González, and T. W. Yiu, “Serious games vs. traditional tools in construction safety training: a review,” *LC3 2017*, vol. 1, pp. 4–7, 2017.

[24] J. W. Burke, M. McNeill, D. K. Charles, P. J. Morrow, J. H. Crosbie, and S. M. McDonough, “Optimising engagement for stroke rehabilitation using serious games,” *The Visual Computer*, vol. 25, no. 12, pp. 1085–1099, 2009.

[25] J. W. Burke, M. McNeill, D. K. Charles, P. J. Morrow, J. H. Crosbie, and S. McDonough, “Augmented reality games for upper-limb stroke rehabilitation,” in *2010 second international conference on games and virtual worlds for serious applications*, pp. 75–78, IEEE, 2010.

[26] L. Griffiths and D. Hughes, “Typification in a neuro-rehabilitation centre: Scheff revisited?,” *The Sociological Review*, vol. 41, no. 3, pp. 415–445, 1993.

[27] J. F. Gubrium and D. R. Buckholdt, *Describing care: Image and practice in rehabilitation*. Oelgeschlager, Gunn & Hain, 1982.

[28] J. Hamari and J. Tuunanen, “Player types: A meta-synthesis,” *Transactions of the Digital Games Research Association*, vol. 1, no. 2, 2014.

[29] M. R. Hassan and B. Nath, “Stock market forecasting using hidden markov model: a new approach,” in *5th International Conference on Intelligent Systems Design and Applications (ISDA’05)*, pp. 192–196, IEEE, 2005.

[30] J. Nealon and A. Moreno, “Agent-based applications in health care,” in *Applications of software agent technology in the health care domain*, pp. 3–18, Springer, 2003.

[31] D. Silver, T. Hubert, J. Schrittwieser, I. Antonoglou, M. Lai, A. Guez, M. Lanctot, L. Sifre, D. Kumaran, T. Graepel, *et al.*, “A general reinforcement learning algorithm that masters chess, shogi, and go through self-play,” *Science*, vol. 362, no. 6419, pp. 1140–1144, 2018.

[32] K. P. Sycara, “Multiagent systems,” *AI magazine*, vol. 19, no. 2, pp. 79–79, 1998.

[33] S. Russell and P. Norvig, “A modern, agent-oriented approach to introductory artificial intelligence,” *ACM SIGART Bulletin*, vol. 6, no. 2, pp. 24–26, 1995.

[34] R. Kucera, “The truth behind facebook ai inventing a new language,” *Towards Data Science*, vol. 7, p. 2017, 2017.

[35] P. K. Murukannaiah, N. Ajmeri, C. M. Jonker, and M. P. Singh, “New foundations of ethical multiagent systems,” in *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*, pp. 1706–1710, 2020.

[36] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, *et al.*, “Human-level control through deep reinforcement learning,” *nature*, vol. 518, no. 7540, pp. 529–533, 2015.

[37] M. N. Shadlen, K. H. Britten, W. T. Newsome, and J. A. Movshon, “A computational analysis of the relationship between neuronal and behavioral responses to visual motion,” *Journal of Neuroscience*, vol. 16, no. 4, pp. 1486–1510, 1996.

[38] M. N. Shadlen and W. T. Newsome, “Motion perception: seeing and deciding,” *Proceedings of the national academy of sciences*, vol. 93, no. 2, pp. 628–633, 1996.

[39] O. M. Andrychowicz, B. Baker, M. Chociej, R. Jozefowicz, B. McGrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, *et al.*, “Learning dexterous in-hand manipulation,” *The International Journal of Robotics Research*, vol. 39, no. 1, pp. 3–20, 2020.

[40] R. K. Srivastava, P. Shyam, F. Mutz, W. Jaśkowski, and J. Schmidhuber, “Training agents using upside-down reinforcement learning,” *arXiv preprint arXiv:1912.02877*, 2019.

[41] L. Engstrom, A. Ilyas, S. Santurkar, D. Tsipras, F. Janoos, L. Rudolph, and A. Madry, “Implementation matters in deep rl: A case study on ppo and trpo,” in *ICLR*, 2020.

[42] T. Chu, J. Wang, L. Codecà, and Z. Li, “Multi-agent deep reinforcement learning for large-scale traffic signal control,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 3, pp. 1086–1095, 2019.

[43] Z. Wang, V. Bapst, N. Heess, V. Mnih, R. Munos, K. Kavukcuoglu, and N. de Freitas, “Sample efficient actor-critic with experience replay,” *arXiv preprint arXiv:1611.01224*, 2016.

[44] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor," in *International Conference on Machine Learning*, pp. 1861–1870, PMLR, 2018.

[45] "Lumosity brain training: Challenge improve your mind."

[46] G. Alankus, A. Lazar, M. May, and C. Kelleher, "Towards customizable games for stroke rehabilitation," in *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 2113–2122, 2010.

[47] O. Delalleau, E. Contal, E. Thibodeau-Laufer, R. C. Ferrari, Y. Bengio, and F. Zhang, "Beyond skill rating: Advanced matchmaking in ghost recon online," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 4, no. 3, pp. 167–177, 2012.

[48] D. Altimira, F. ueller, G. Lee, J. Clarke, and M. Billinghurst, "Towards understanding balancing in exertion games," Association for Computing Machinery, 2014.

[49] J. W. Houriet Jr, J. C. Nydick, D. L. Hedin, D. L. Aymar, T. R. Horne, and R. H. Wiles, "System for handicapping substitute or unranked players in a dart game match," June 13 2000. US Patent 6,076,021.

[50] "Desktop operating system market share worldwide," Jun 2020. https://gs.statcounter.com/os-market-share/desktop/worldwide.

[51] Limdingwen, "limdingwen/steam-engines," Jun 2018. https://github.com/limdingwen/Steam-Engines.

[52] SoloGameStudios, "Comparison of game engines 2020," Apr 2020. https://indiegamedev.net/2020/02/11/comparison-of-game-engines-2020/.

[53] "Cognitive rehabilitation software," May 2020. https://www.rehacom.co.uk/.

[54] "Neuronup. web platform of cognitive rehabilitation," May 2020. https://www.neuronup.com/.

[55] D. Neumann, H. J. Westerhof-Evers, A. C. Visser-Keizer, L. Fasotti, M. C. Schönherr, M. Vink, J. van der Naalt, and J. M. Spikman, "Effectiveness of a treatment for impairments in social cognition and emotion regulation (t-scemo) after traumatic brain injury: a randomized controlled trial," *Journal of Head Trauma Rehabilitation*, vol. 32, no. 5, pp. 296–307, 2017.

[56] "Infoteste," May 2020. https://www.infoteste.pt/.

[57] "Cognifit." https://www.cognifit.com/.

[58] J. Whyte, "Traumatic brain injury rehabilitation: are there alternatives to randomized clinical trials?," *Archives of physical medicine and rehabilitation*, vol. 83, no. 9, pp. 1320–1322, 2002.

[59] J. S. Schiller, J. W. Lucas, and J. A. Peregoy, "Summary health statistics for us adults: national health interview survey, 2011," 2012.

[60] G. S. Griesbach, L. A. Kreber, D. Harrington, and M. J. Ashley, "Post-acute traumatic brain injury rehabilitation: effects on outcome measures and life care costs," *Journal of neurotrauma*, vol. 32, no. 10, pp. 704–711, 2015.

[61] D. of Health Human Services, “Acquired brain injury,” May 2014.

[62] M. G. B. D. B. Miller, J. P. S. Fleminger, G. T. S. Thornhill, J. P. JH. Olver, F. M. JM. Mazaux, A. V. A. Hodgkinson, L. R. SJ. Vangel, A. G. VL. Phillips, D. P. CM. Cameron, J. Ghajar, and et al., “Direct cost associated with acquired brain injury in ontario,” Jan 1970.

[63] S. K. Numrich, “Culture, models, and games: Incorporating warfare’s human dimension,” *IEEE Intelligent Systems*, vol. 23, no. 4, pp. 58–61, 2008.

[64] Openai, “openai/gym,” May 2020. https://github.com/openai/gym.

[65] “The code affirms an obligation of computing professionals to use their skills for the benefit of society..” https://www.acm.org/code-of-ethics, Code of Ethics.

[66] “Effective therapy for cognitive impairments.” https://www.schuhfried.com/cogniplus/.

[67] “Pland – executive functions: Planning and action skills.” https://www.schuhfried.com/cogniplus/trainings/pland/.

[68] “Names – long-term memory: Learning of face-name associations.” https://www.schuhfried.com/cogniplus/trainings/names/.

[69] “Coding – working memory: Spatial coding.” https://www.schuhfried.com/cogniplus/trainings/coding/.

[70] “Intrinsic motivation inventory (imi).” https://selfdeterminationtheory.org/intrinsic-motivation-inventory/.

[71] D. Markland and L. Hardy, “On the factorial and construct validity of the intrinsic motivation inventory: Conceptual and operational concerns,” *Research quarterly for exercise and sport*, vol. 68, no. 1, pp. 20–32, 1997.

[72] R. M. B. Rocha, *Jogos sérios para reabilitação cognitiva*. PhD thesis, 2015.