Universidade do Minho
Escola de Engenharia
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Biometric Analysis of Behaviours in Serious Games

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Master dissertation
Master Degree in Informatics Engineering

Dissertation supervised by
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April 2022

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ABSTRACT

This document is a Master's Dissertation, within the scope of data analysis for visualisation and exploration of knowledge in the health area.

The thesis herein described is part of the second year of the Master's in Informatics Engineering, and it was held at the University of Minho in Braga, Portugal.

The main objective of this project is to combine the data measuring the performance of a patient when he is playing a specific game with the data collected at the same time from some biometric sensors so that it is possible to apply data analysis algorithms in order to discover new relationships between the data. It is also intended that, through adequate visualisation, knowledge can be created. Data collection was carried out in partnership with the *Centro Neurosensorial de Braga*.

For data collection, initially, it was used an emotion recognition activity, a test that measures the processing speed (quick naming) and two tests to better characterise the child in terms of memory and attention capacity.

Initially, a small analysis was made of the data that were extracted through the platform provided by the *Centro Neurosensorial de Braga*. After a mass data collection, its analysis was carried out.

It was possible to verify, analytically, that as the memory deficit increases, among others, the number of fixations, the number of regressions, the time taken to perform the rapid naming test increases. Regarding the emotions expressed during the rapid naming test, it was possible to verify that respondents who expressed happiness during the test show a better memory capacity, while children who expressed emotions of surprise or sadness are subject to memory deficit.

Keywords: Data Analysis, Data Visualisation, Knowledge Exploration, Health Care.

RESUMO

Este documento é uma Dissertação de Mestrado, no âmbito da análise de dados para visualização e exploração do conhecimento na área da saúde. A tese aqui descrita insere-se no segundo ano do Mestrado em Engenharia Informática e foi realizada na Universidade do Minho em Braga, Portugal.

O principal objetivo deste projeto é combinar os dados que medem o desempenho de um paciente durante a realização um jogo específico com os dados recolhidos, ao mesmo tempo, de alguns sensores biométricos, para que seja possível aplicar algoritmos de análise de dados a fim de descobrir novas relações entre os dados. Pretende-se também que, através de uma visualização adequada, o conhecimento possa ser criado. A recolha de dados foi realizada em parceria com o *Centro Neurosensorial de Braga*. Para a recolha de dados, inicialmente, opta-se por usar uma atividade de reconhecimento de emoções, uma prova que mede a velocidade de processamento (nomeação rápida) e duas provas para caracterizar melhor a criança quanto à sua capacidade de memória e de atenção. Inicialmente, foi feito uma pequena análise dos dados que eram extraídos através da plataforma disponibilizada pelo Centro Neurosensorial de Braga. Depois de uma recolha de dados em massa, foi feita a sua análise.

Foi possível verificar, analiticamente, que à medida que aumenta o défice de memória aumenta, entre outros, o número de fixações, o número de regressões, o tempo de realização da prova da nomeação rápida. Em relação às emoções expressas durante a prova de nomeação rápida, foi possível verificar que os respondentes que expressaram felicidade durante a prova mostram uma melhor capacidade de memória, enquanto as crianças que expressaram emoção de surpresa ou tristeza têm tendência a ter uma menor capacidade de memória.

Palavras-Chave: Análise de Dados, Visualização de Dados, Exploração de Conhecimento, Cuidados de Saúde.

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ACRONYMS

A

AI Artificial Intelligence.

API Application Programming Interface.

B

BANC Coimbra Neuropsychological Assessment Battery.

BPM Beats Per Minute.

C

CNB Centro Neurosensorial de Braga.

CRISP-DM Cross-Industry Standard Process for Data Mining.

D

DM Data Mining.

S

SPO2 Peripheral Oxygen Saturation.

1

INTRODUCTION

This first chapter introduces the project, along with the motivations, objectives, methodology, and document structure.

1.1 MOTIVATION

In the academic year 19/20, at the request of Dr[a] Ana Paula Azevedo, from the *Centro Neurosensorial de Braga*, three MiEI/MEI student groups developed three serious games, within the scope of the 4th/1st year (LEI) projects, to recognise forms and emotions, and to train the central and peripheral vision. These games are aimed at memory therapy, inattention, dyslexia, and other problems that affect the acquisition of knowledge in the learning processes.

Serious games are used in several areas, such as health, education, military, and government (Rego et al., 2016; Gaggi et al., 2017; Rego et al., 2010). Over the past few years, serious games have been developed for use in therapy and prevention of cognitive diseases. This type of games is used as an alternative to traditional therapy, as they have an interactive component that makes the learning process pleasant and dynamic, making the patient remain interested and motivated during therapy (Rego et al., 2016; Zayeni et al., 2020).

If during the game, the patient's data is measured, such as score, time, amount of wrong response and, through sensors, the tracing of the eye path, balance, and heart rate, the disease level and the therapy can be assessed. The use of cardio sensors is relevant for the recognition of the emotional states of each patient because the emotions can affect a person's physical performance. A study (Rathschlag and Memmert, 2013), by German Sport University, concluded that people in a state of anger or happiness perform better than individuals in a state of anxiety or sadness.

To obtain useful information through the collected data, a DM process can be used, as this aims to acquire new knowledge through large amounts of complex data (Gosain and Kumar, 2009; Ilayaraja and Meyyappan, 2013). The DM process has been widely used in the research of health problems, and cognitive diseases belong to an area that can benefit from the aid of the techniques of this process (dos Santos et al., 2019).

There are several methods of data mining, such as classification, clustering, association, and patterns (Pujari, 2001). These can be divided into supervised and unsupervised learning. dos Santos et al. (2019) concluded that the 3 most used techniques in supervised learning are Support Vector Machine, Decision Tree and Random Forest, followed by logistic regression, Naïve Bayes and artificial neural networks. For the unsupervised, the most used techniques, are K-Means Clustering, Least Absolute Shrinkage and Selection Operator and Association Rules.

For the realisation of DM techniques, there are several tools on the market and you will have to choose one to do the job. The 3 most used tools are R, Weka, and Python (dos Santos et al., 2019).

R and Python are simple and dynamic programming languages. R is a statistical language, and one of the strengths is the simplicity with which quality graphics can be created [1]. Python is a high-level object-oriented language, and it has a simple and easy to learn syntax [2]. The Weka tool is open source software used through a graphical interface, a terminal, or a Java API [3]. There is also the Rapidminer software, used in the first year of the master's degree in the discipline of knowledge discovery. The main goal is to make the predictive analytics process faster and easier to use in business scenarios (Hofmann and Klinkenberg, 2016).

The Weka and Rapidminer tool is recommended for people who are not so interested in programming, while R and Python are necessary to program (dos Santos et al., 2019). These tools can implement different data mining methods, and the algorithms they use can change.

The visualisation process is essential, as it helps to understand relationships in the data, to identify patterns, and to group many points, being fundamental for the discovery of knowledge and in decision making (Chawla et al., 2018). But as the big data has been developing fast, it may have problems in visualising data such as visual noise, large image perception, loss of information, high rate of image change, and high-performance requirements (Hajirahimova and Ismayilova, 2018; Gorodov and Gubarev, 2013).

There are several classic methods of visualising data such as line and bar graphs, Scatter and bubble plots, charts, tree map, and Sunburst. These more traditional methods sometimes do not help to solve specific problems, so there was a need to introduce new data visualisation methods, such as tag cloud, clustergram, motion graphics, panel and history flow (Hajirahimova and Ismayilova, 2018).

As serious games have become a complement for the treatment of diseases of the neurological lining, it is hoped that with this project new knowledge can be acquired, with the clinical data provided, that is relevant for decision-making in the therapy of each user.

1 https://www.r-project.org/about.html
2 https://www.python.org/doc/essays/blurb/
3 https://www.cs.waikato.ac.nz/ml/weka/index.html

1.2 OBJECTIVES

The objectives for this master's thesis are as follows:

- To study the significance of using data mining techniques in health, focusing on the area of cognitive diseases.
- Find the best solution to extract knowledge, through data mining algorithms and/or statistical analysis, from the patient's datasets provided by the *Centro Neurosensorial de Braga* (data concerned physical/emotional behaviour collected by biometric sensors, as well as, data concerned with the performance of the game Player).
- Apply the selected approaches to extract knowledge relating the performance of a patient when executing a given exercise to train his mental capabilities and his emotional behaviour.
- Exhibit the inferred knowledge extracted in an adequate visual interface.

1.3 RESEARCH HYPOTHESIS

With this master's work, it will be intended to see how best to extract knowledge, through the data of the different tests. Data will be collected such as the number of points, fixations, BPM, general classification, total errors and duration, among others, from biometric sensors and the general performance obtained in the activity. With the analysis of these data, it is intended to improve the diagnosis of attention deficit and memory.

1.4 RESEARCH METHODOLOGY

For this Master's work, it will be followed a methodology based on literature review, solution proposal, implementation and test. This approach consists of the following steps:

- Bibliography search on: serious games; use of sensors for therapy; data mining process in healthcare.
- Study and synthesise of the selected bibliography.
- Identification and analysis of the sensors available in *Centro Neurosensorial de Braga*, the formats used to export data and the parameters necessary to understand the patient's behaviour.
- Develop a strategy and propose a solution.

- Implement the solution using the adopted tool.
- Test and refinements.
- Results evaluation and discussion.

1.5 DOCUMENT STRUCTURE

This document is organised into five chapters. In Chapter 1, the problem and motivation and the objectives of this thesis are presented. Chapter 2 presents the state of the art of serious games on health, eye movements, eye movement detection sensor, emotions and, data mining. In Chapter 3 is presented the architecture of the solution proposal, and which skills and variables one wants to evaluate in this project. Chapter 4 presents a short study of the dataset data and some results that can be extracted through it. Chapters 5, 6 and, 7 show the application of different techniques to extract new knowledge through different datasets. The Chapter 8, presents the reapplication of part of the study described in Chapter 7, in a new population and in the total population used in this thesis to try to reinforce the results. The Chapter 9 presents the conclusions, the contributions and the future work.

2

STATE OF THE ART

With the evolution of technology, society increasingly seeks to adapt to the technological environment. In the area of health, this adaptation made it possible to improve and perfect traditional therapies.

An example of it are serious games. With the greater use of video games, games have been created that are not just for fun, but to help the rehabilitation of some diseases, such as Big Brain Academy (treat cognitive impairment) or WiiFit (for movement disorder).

Several types of serious games have been developed, depending on which factors they train, such as concentration, abstraction, memory, visuo-spatial function, persistence, hand coordination, space delimitation, motor skills, different reactions are promoted. These also allow measuring variables like the mouse's position, response time, errors and successes, contributing to a better assessment of the patient's performance during the game. For the same purpose, sensors are commonly attached, such as the eye-tracker or Kinect. Thus, studies have been developed to understand the advantages of its application in the treatment of various diseases, namely as a complement or even a substitute for conventional therapies.

2.1 SERIOUS GAMES

Serious games were created with a different purpose than entertainment. Serious games are games, which have mechanisms that aim at something or produce a common good, in users, covertly in the activities of the game. In these types of games, if the player is motivated and entertained, he will continue to play repeatedly. This way, they will do something useful that they would not normally do, thus achieving the goal of serious games. (Gaggi et al., 2017).

Over the years, the use of serious games has increased rapidly due to the growth of video games. These games have different areas of use, such as health, education, military and government (Rego et al., 2016; Gaggi et al., 2017; Rego et al., 2010).

In health, serious games are increasingly used. There is a wide variety of areas in health that these can be used for, such as physical rehabilitation, cognitive rehabilitation, therapy and medical training. This theme will be developed in the next subsection. In the area of education, serious games are used to help in the development of communication, group decision making, strategy, among other skills (Susi et al., 2007). The military has used games to train its strategies for many years. Nowadays, the growth of technology has made these games evolve in a complex way, and there are now simulators for tanks or group training (Susi et al., 2007). Thus, these games portray scenarios from the real world, simulating aspects at the tactical, strategic and operational level, which prepare the military for combat in the war (Samčović, 2018). In the government category, games can be both training and simulations, including tasks such as dealing with terrorist attacks, urban planning, budget balance, traffic control. This type of training ends up having a lower cost, as it does not involve so many human and material resources (Susi et al., 2007).

In this thesis, the work focuses on serious games in the health area with a focus on therapy.

2.1.1 *Serious Games in health*

Serious games in the health field can be used to train professionals, in procedures or simulations of real-life experiences, as well as in the therapy of some diseases or rehabilitation in patients (Gaggi et al., 2017).

These games are important in the training of professionals, as some procedures or situations require some skill on the part of the professional, and it is convenient to be trained before putting them into practice (Esteban et al., 2011; Gaggi et al., 2017).

For therapy or rehabilitation of patients, these games have advantages because they contain hidden exercises that help in rehabilitation, encouraging patients to perform these tasks playfully (Gaggi et al., 2017).

Rehabilitation in patients with some disability has a better result with more intensive training where a set of specific tasks is accomplished to achieve a goal. This type of approach has as treatment the repetition of tasks that makes the patient unmotivated in the execution of these tasks (Rego et al., 2010).

Games manage to engage the person's attention and, most provide different levels, which gives the feeling of challenge and the ability to adapt to the capabilities of each player. Through serious games, the patient will be able to take the same approach in therapy, but more interactively becoming less boring for the patient.(Rego et al., 2010)

2.2 EYE MOVEMENT

Eye movements can be divided into two broad categories, saccadic movements and stabilisation movements.(Singh, 2012; Cheng and Vertegaal, 2004). The first bring objects of interest to the area of sharp vision, include saccades and vergence movements. The second try to fix the image on the retina; include fixations, and smooth pursuit movements. (Singh, 2012)

Saccades

Saccades are the most common eye movements and the most significant to comprehend the scene perception (Rayner and Pollatsek, 1992). These are fast and accurate (Singh, 2012), occurring during one fixation and the following (Carter and Luke, 2020). These movements are the support for visual exploration, due to the repositioning of the eye fovea between places of interest within the optical space (Stuart et al., 2019; Singh, 2012).

The velocity and duration of the saccade are a function of the distance moved (Carter and Luke, 2020; Rayner, 2009). A reading saccade lasts about 30 ms and corresponds to a rotation of 2 degrees, while if it is a saccade of scene perception corresponds to 5 degrees of rotation and lasts between 40 and 50 ms (Abrams et al., 1989; Rayner, 1978).

Saccadic movements are relevant for the investigation, as the deficit in saccadic function can be used to perceive cognitive or visual processes helping in the neurological diagnosis or even to understand some deficits in daily tasks (Stuart et al., 2019).

Fixations

A fixation corresponds to the time interval in which a target of interest is kept stable on the retina, that is, the eyes are fixed on an object. In a single fixation, the eye cannot acquire quality information from the entire visual field, which causes the eyes to move repeatedly. The size of a fixture varies depending on the quality of the information processed(Carter and Luke, 2020; Singh, 2012).A fixation can last between 100ms to 1000ms, but usually lasts between 180ms and 330ms (Rayner, 2009).

Other movements

As previously mentioned, although saccades are one of the most investigated types of movements, there are other movements of the same kind, such as:

- Smooth pursuit, follows a slow-moving object, preserving the image of the stable target on the retina. It can follow a target moving between 5 and 30 deg/s.
- Vergence, is the movement of rotation of the eyes to fix the same point in space. For closer targets, the eyes rotate towards each other, and for more distant targets they turn oppositely.

2.3 EYE TRACKER

Eye tracking is the procedure of recording the movement of the eyes and locating where the person is looking at during the time of a specific task (Singh, 2012; Carter and Luke, 2020). During the 20th century, several methods for measuring eye movements were developed, but these were expensive and quite laborious, which was a barrier for researchers.

Today, with the advancement of technology, it has become easier to track eye movement (Carter and Luke, 2020).

An eye tracker can measure eye movements, as the position of the eye can be mapped several times per second. This, through software, also manages to make a visual map of how the person saw the elements of the scene.[1]

Nowadays, eye trackers illuminate the eyes with a light source, usually infrared because it is invisible to our eyes. The light it is reflected off the cornea and through the software calculates the position of the eye (Brunyé et al., 2019; Carter and Luke, 2020).[1]

There are different eye trackers devices and, although they have the same operating principle [1], each has its advantages and disadvantages such as speed, accuracy and cost (Brunyé et al., 2019). As mentioned on the TobiiPro website [1], these can be divided into different groups, the main ones are webcam- composed solely by the webcam, these do not have sensors or specialised cameras; Screen-based - it's a smaller panel that can be connected to a laptop, are remote and stand-alone; Wearable- includes devices such as eye-tracking goggles from virtual reality headphones.

Eye trackers can collect different measures that help you understand the behaviour of the interpretive process. The most common metrics are the number of fixations, the number of regressive fixings, duration of fixations, amplitude, the peak speed of saccade, blink rate, blink amplitude and duration, phasic and tonic pupil diameter (Brunyé et al., 2019).

2.4 EMOTIONS

According to Gazzaniga et al. (2005), emotions are an instant reaction to a specific event. As it is a spontaneous event, it means that we do not choose to feel the emotions. Emotions can be confused by a sensation or mood. As stated by the group Paul Ekman, emotions does not last more than an hour without interruption and if it persists for a long period without suspension, it can be considered humour[2].

The theme of emotions is a subject in which there is no consensus between the different areas of knowledge (Lang, 1995) there is no one theory that is general or accepted throughout the world.

2.4.1 *Classification*

For the classification of emotions there are two theories, basic emotions theory and dimensional theory, which are the most accepted in studies on emotions (Gu et al., 2019).

In the theory of basic emotions, the predominant idea is that humans have a limit of emotions, these manifest a recurrent pattern with associated behavioural elements. Although this theory is accepted by many, there is still controversy regarding how many basic emotions

1 https://www.tobiipro.com/blog/what-is-eye-tracking/
2 Source: https://www.paulekman.com/universal-emotions/ , accessed on 27/04/2021

there are. According to Ekman (1992), initially, a list was made, of six basic emotions (angry, fear, sadness, disgust, happiness, surprise), represented by facial expressions as shown in Figure 1 [3], where later evidence was found that distinguished disgust from contempt. These emotions overcome cultural, ethnic, linguistic and regional differences [2].

Figure 1: The six basic emotions

There were also those who proposed 8 basic emotions: anger, joy, fear, disgust, sadness, confidence, surprise and anticipation (Gu et al., 2019). Jack et al. (2014) in a recent study, they showed that anger and disgust and surprise share similar expressions, eventually proposing that humans only have 4 basic emotions: fear, anger, joy and sadness. Other authors such as Izard, Panksepp & Watt, Leveson suggest some different basic emotions and reject others. Some of the emotions have different names but represent the same. Figure 2 shows a table taken from Tracy and Randles (2011), where you can see the emotions that the 3 previous authors and Ekman & Cordaro suggest can be seen. In Figure 2, the names of emotions with the exclamation point ("?") are emotions in which the authors indicate that there is still no clear supporting proof.

Theoretically and empirically supported basic emotions according to each model			
IZARD	PANKSEPP & WATT	LEVENSON	EKMAN & CORDARO
Happiness	PLAY	Enjoyment	Happiness
Sadness	PANIC/GRIEF	Sadness	Sadness
Fear	FEAR	Fear	Fear
Anger	RAGE	Anger	Anger
Disgust		Disgust	Disgust
Interest	SEEKING	Interest?	
Contempt?			Contempt
	LUST	Love?	
	CARE	Relief?	Surprise

Figure 2: Similarities and differences between the basic emotions suggested by the 4 authors.

3 Source: https://managementmania.com/en/six-basic-emotions , accessed on 20/01/2021

Dimensional theory began to be studied by Wundt and later by Scholsberg who suggested 3 dimensions for emotions (pleasant-unpleasant, tension-relaxation and calm-excitement). Ekman later proposed only two dimensions, pleasant-unpleasant and active-rest, since tension-relaxation and excitation-quiet meet in the same dimension (Gu et al., 2019). Later, Russell (1980) created the circumplex model for emotions that contain two independent dimensions, pleasure - displeasure and rest - active, represented in Figure 3 [4] .

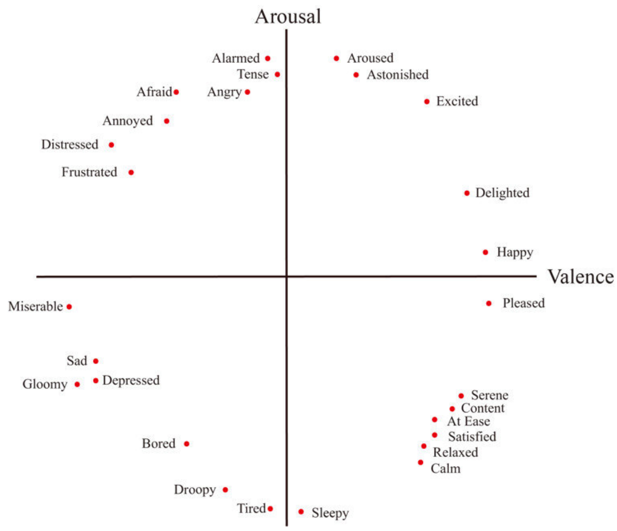


Figure 3: The circumplex model developed by James Russell

Although the two theories are different, as the first proposes a limited number of emotions and the second suggests that emotions vary depending on pleasure and intensity, the basic emotions can lie along the axes of the circumplex model, leading (Gu et al., 2019) to reinforce the idea of that there are four basic emotions: fear, anger, sadness and joy. The remaining emotions, included in the quadrants of the model proposed by Russell, can be called complex emotions, which according to Ekman is a conjugation of elements of the basic emotions.

2.4.2 *Theories*

As mentioned above, there is still no consensus on the subject of emotions and therefore there are several theories about how emotions are generated.Next, 3 theories are presented.

James-Lange Theory

Common sense tells us that we feel something, so we express emotion and, our body responds to that emotion. William James created a contradictory argument, where he says that humans perceive the stimulus, where there is a physical change, which makes us feel an emotion (Gazzaniga et al., 2005; Miguel, 2015). That is, "we feel sad because we cry, we

4 Source: https://www.researchgate.net/figure/Russells-circumplex-model-The-circumplex-model-is-developed-by-James-Russell-In-the_fig1_330817411 , accessed on 01/09/2021

feel angry because we fight" are some examples given by James. Around the same time, Carl Lange suggested an identical theory, so this theory became known as the James-Lange theory of emotions (Gazzaniga et al., 2005).

Cannon-Bard Theory

Walter Cannon and Philip Bard objected to the James-Lange theory giving rise to a new theory, the Cannon-Bard theory of emotion. These admitted that the body responds to an experience more slowly than our mind. They also believed that there were some emotions the body responded to similarly. Cannon and Bard suggested that physical reactions and emotions occur at the same time but independently, meaning that information about emotions is sent separately but simultaneously to the body and mind (Gazzaniga et al., 2005).

Schachter-Singer's Two-factor Theory

Stanley Schachter and Jerome Singer believed some points of the theories mentioned. Regarding the James-Lange theory, they think it is correct in comparing the body's reaction to an emotion. And regarding the Cannon-Bard theory, they agreed that there was no specific pattern for each emotion, as there were many emotions. So they suggested that emotional stimuli would have almost the same physiological response, that response when the situation is interpreted differently and given a label. This theory was called the two-factor theory of emotion. (Gazzaniga et al., 2005)

2.5 DATA MINING

Due to the rapid growth of technology, nowadays, there is no shortage of data. Thus, it was necessary to create methods and tools to facilitate data processing and knowledge discovery (Jun Lee and Siau, 2001). DM, as mentioned in section 1.1, is a process of analysing large amounts of data that aims to find patterns, relationships, and trends that are useful to extract new knowledge (McClean, 2003; Schuh et al., 2019).

The DM process is based on data pre-processing, exploring, finding patterns and applying them. One of the existing DM processes is the Cross-Industry Standard Process for Data Mining (CRISP-DM). This involves business understanding, data understanding, data preparation, modelling, evaluation and deployment (Figure 4[5]). Business understanding is where the objectives and requirements of the project are understood, and the objective of data mining is determined. Data understanding explores data and identifies data quality problems. Data preparation is the stage in which data are cleaned selected along with attributes. In the modelling stage, the DM models are chosen, and this is where their construction and evaluation takes place. Evaluation is where results are evaluated, and

5 Adapted from: https://www.datasciencecentral.com/profiles/blogs/crisp-dm-a-standard-methodology-to-ensure-a-good-outcome

the process is reviewed. Finally, in Deployment, the models are put into practice, and the models are monitored and maintained (Wirth and Hipp, 2000).

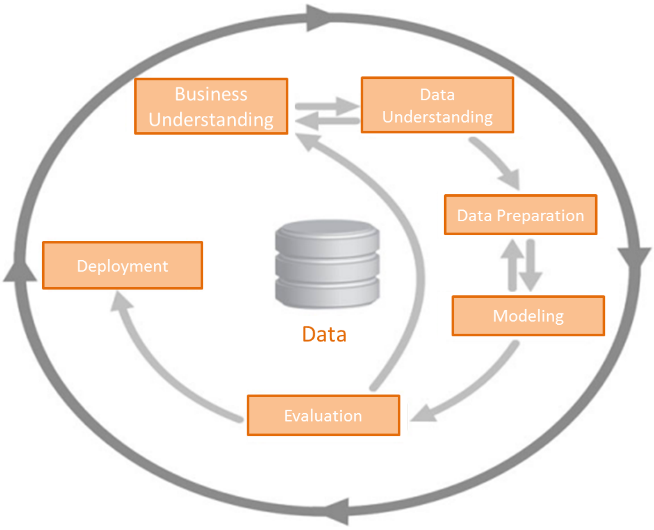


Figure 4: The CRISP-DM Process.

2.5.1 *Techniques and Algorithms*

There are several DM techniques and algorithms, such as regression, classification, clustering, association rules, genetic algorithms, among others.

Clustering

Clustering techniques help to identify groups (regions) in the data set, which allow finding a pattern and correlations between the data. Clustering features, among others, the following methods:

- Grid-based
- Mode-based
- Density-based methods

Association rules

Association rules are often used to discover patterns in learning systems. Usually, the association rules algorithms tend to generate many rules where often a part of them doesn't have much value. Normally, a rule is evaluated through the confidence and support threshold, although there may be other variables that can influence it.

Classification

This technique, one of the most used in DM, involves learning and classification. Rules created through the training dataset are evaluated for their accuracy. If the precision values of these are acceptable, then they will be applied. The most used models in this technique are:

- Decision trees
- Support Vector Machines
- Neural Networks
- Bayesian Classification

2.5.2 *Application Areas*

Nowadays, Data Mining is applied in several areas, such as industry, business and medicine. In industry, for example, classification techniques and induction rules are used for quality control. In the business area, Data Mining can be applied in different areas such as marketing to create a profile of consumers. In medicine, it is used to categorise diagnoses, treatments and monitoring. The use of DM in this area is very promising for the evaluation of treatments, as it is necessary to cross different datasets with many attributes and different time intervals (McClean, 2003).

3

PROPOSED APPROACH

In this chapter, after an extensive review of what has already been published in this area, the proposed solution for this Master's project will be presented. It will be addressed the data collection, the DM process, and data visualisation to extract new knowledge.

Game skills and variables to be studied in this project will also be presented.

3.1 ARCHITECTURE

For the extraction of knowledge, using biometric data collected while playing serious games, it is thought to collect data from various experiences of some children between 5 and 12 years old. The collected data will come from sensors such as the eye tracker, the webcam, the monitor, and from a cardio sensor. These collected data are stored in a database, and later, some metrics and statistics are calculated. To obtain the data in JSON format, it is possible make the call to the API, as mentioned in the section 4.2.1, being able to take the data with the calculation of the metrics or the data without these metrics. After this process, a DM process will be applied, and later data visualisation methods will be applied for the knowledge to be created. The data collection system is already implemented and used by the CNB. The architecture described above is represented in Figure 5.

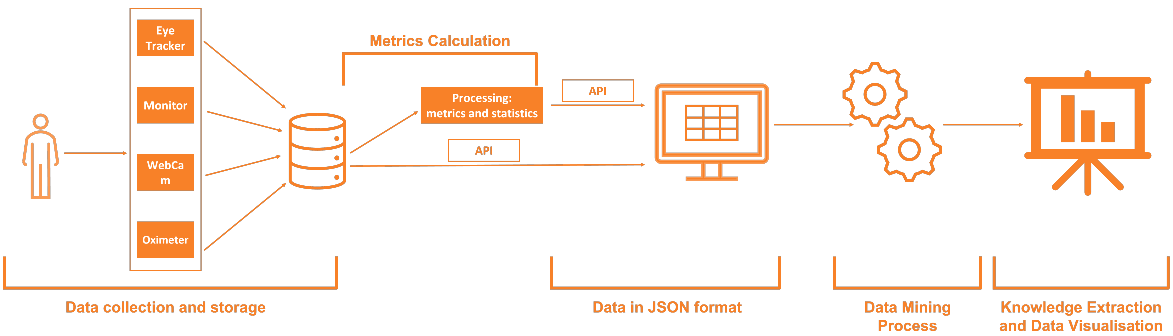


Figure 5: The proposed System Architecture.

3.2 THE SKILLS AND VARIABLES MEASURED DURING THE SERIOUS GAME

As mentioned in the state of the art (Chapter 2), several studies have in mind that, at the cognitive level, serious games can have several benefits. For these studies, kids would do two different activities. One would be an emotion recognition activity, consisting in identifying the face that better represents the requested emotion (eight in total). The other one would be a more serious activity, like the BANC's Rapid Naming tests. This type of serious game trains:

- Concentration
- Quick thinking
- Abstraction
- Development of visual skills
- Persistence

Regarding the variables measured during the game, as described in BANC, information such as duration, errors, omissions, and successes will be collected.

For sensors, it was decided to collect the following:

On The Eye Tracker

- Coordinates and Position of points and fixations
- Time of point or fixation occurrence
- Duration of fixation

With the data from the eye tracker, it is possible to calculate new metrics or use those that are processed before obtaining the JSON file, as shown in Metrics Calculation - Figure 5. These metrics are detailed in section 4.2.1.

On The WebCam

- Recognition of emotions like as anger, fear, contempt, disgust, sadness, happiness,surprise and neutral.

This recognition of emotions is done with images taken every 0.5s, of the person during the game, and later the facial recognition of emotions is made through the processing of this (Metrics Calculation - Figure 5).

On The Cardio Sensor

- Heart rate

- Blood oxygen saturation

This data collection is done through an oximeter, where data from 100 patients can be stored. At the end, the data obtained can be collected every 2 seconds.

The variables measured during the game were determined taking into account the different studies read for Chapter 2 and with the feedback from the *Centro Neurosensorial de Braga*.

3.3 AZURE FACE SERVICE

The data collection system, already implemented at the CNB, uses Microsoft Azure's cognitive services to detect emotions. The Azure Face Services is part of the cognitive services. This service contains AI algorithms to detect, analyse and recognise faces in images.

From the aforementioned service, the API Detect was used to detect emotions. This API uses 27 facial points as a reference and which are simple to recognise on a face, such as pupils, eyebrows or the tip of the nose (Figure 6 [1]). Using this API it was obtained, for each face detected in the image, the following attributes a FaceID, an age estimate, a list of emotions, the gender, if you wear glasses and what type of glasses, among others.

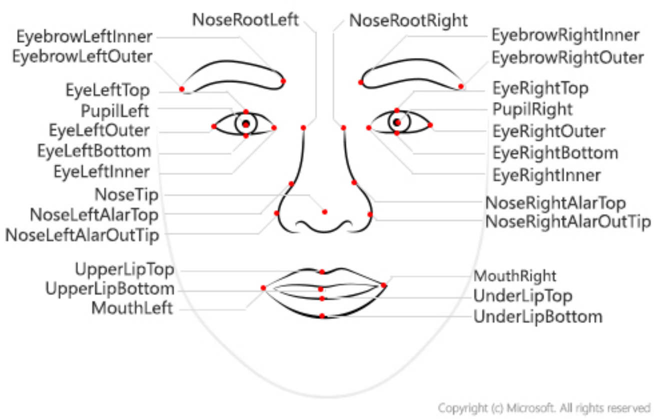


Figure 6: Face landmarks.

1 Source: https://docs.microsoft.com/en-gb/azure/cognitive-services/face/concepts/face-detection, accessed on 27/04/2021

4

FIRST DATA ANALYSIS

In this chapter, is described that the study was carried out to become familiar with the data collected through the sensors. In this study, oximeter data have not yet been included.

4.1 STUDY DESCRIPTION

This study, was carried out using data collected from patients at the CNB. Five random executions of children were chosen. Two of these children are 7 years old the remaining 3 children are 8, 9 and 12 years old.

4.1.1 *Exercises used, images*

In this study, only data collected with the exercise of naming numbers, emotions and direction were used, as shown in Figure 37 (Appendix A). Taking as an example the first line of the exercise, the child will have to say "Happy, five, left, three, one".

4.2 COLLECTED DATA

In this section, it will be explained how the data was obtained and what corresponds to each one of them.

4.2.1 *Data of the eye tracker*

To obtain the raw data for an execution, a GET call must be made to the API identifying an execution (e.g: "/api/experimentsInstances/<execution id>/download/data?Type=csv"). This returns all points, fixations and frames of the camera recorder.

For each data entry, the following is obtained:

- An 'Id', to identify whether it is a point, or a fixation, or a frame of the camera recorder;

- A 'Timestamp',
- A 'Value' containing data, such as, device timestamp, absolute X coordinate, absolute Y coordinate, X coordinate relative to experiment, Y coordinate relative to experiment, X position in percentage (0 to 1) relative to experiment, Y position in percentage (0 to 1) relative to experiment, a flag that says whether the point is within the experience (0/1). For a fixation, the 'Value' has one more value, the duration of fixation in ms. If 'Id' is 'camerarecorder.frame', 'Value' contains only the binary data from a .jpg file.

To get some metrics from the executions, it is necessary to make a GET call to the API also identifying an execution, but using "/api/experimentsInstancesMetrics?Filter={"experiment_instance ":<execution_id>}&range=[0,499]&sort=["id","ASC"]".

This returns a list containing nine elements in JSON format. The first includes all points within the experiment, giving information about the coordinates and normalised coordinates of each point, and a timestamp. The second contains all the fixations that are within the experiment, including the information of the fixation coordinates, the standard fixation coordinates, a timestamp and the fixation duration. The next JSON provides information on how many fixations occurred during execution. In the fourth, return the number of fixations that occurred in the different zones defined in the experiments. The fifth element provides the duration of the fixations in each zone. The sixth JSON contains the total points by zones. The seventh contains the duration of the points in the different zones. The penultimate one includes a list of zone changes. And, in the last one, there is the data on the patient's emotions during the execution.

4.3 Applied techniques and results

For the data described above, some analyses were made, which will be described below.

For each execution, data can be calculated such as, how many points and fixations occur outside the image of the experiment, the total number of points or fixations and build a map with the points and the fixations (Figure 7).

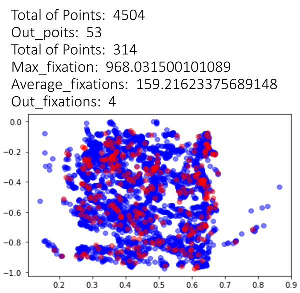


Figure 7: Map with points and fixations

It is also possible to extract information like as the largest, the smallest and, the average distance of the points or the fixations, as shown in the same figure. Through the time of occurrence of each point and fixation, it is possible to determine the duration of the activity in seconds and, the average of these occurred per second, as shown in in Figure 8.

ID: 54
Total Points and Fixations: 4818
Total Points: 4504
Total Fixations: 314
Total_time: 0:01:40.407000
Total_time in seconds: 100.407

Points
Max_Dist: 0.5300472258373291
Min_Dist: 0.0
Average_Dist: 0.013142576612410427
Average_PointsPerSeconds: 44.8574302588465

Fixations
Max_Dist: 0.3271293591063674
Min_Dist: 0.0008100979031356038
Average_Dist: 0.08366281431542372
Average_FixationsPerSeconds: 3.127272002948002

Figure 8: Calculated data

Using the emotions that each child had throughout each execution, an emotion correlation map was used. Different maps were created, one with all the emotions of the 5 executions and one for each execution.

There are two types of correlation, the positive correlation which means that if the value of one increases, the value of the other also increases, and there is the negative correlation that when the value of one increases that of the other, it tends to decrease. Figure 9 shows that the emotions that have the most positive correlation are the emotions disgust with the emotion anger and contempt. The emotion neutral have the biggest negative correlation comparative to the others emotions.

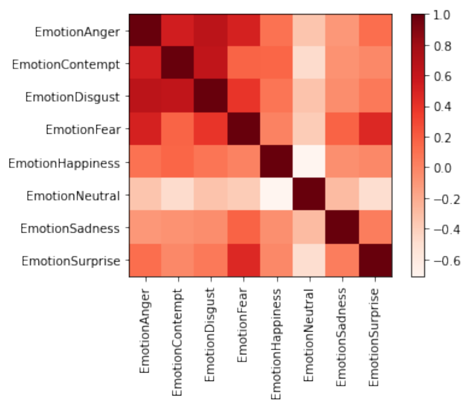
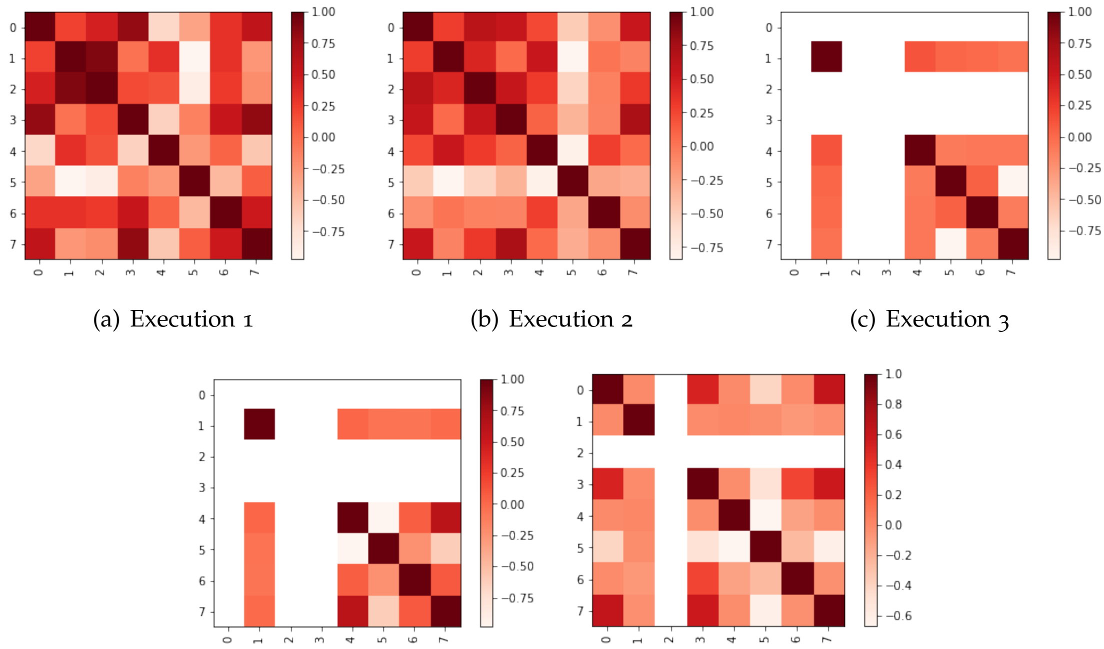


Figure 9: Correlation map of emotions of the five executions

Analysing each execution separately, it is noted that the map of the first two executions behaves identically to the map of correlations of all runs (look at Figure 10(a) and 10(b))[1]. In the other 3 executions, it is possible to see that there are emotions that don't correlate with the others (shown in Figure 10(c) to 10(e))[1].



(a) Execution 1 (b) Execution 2 (c) Execution 3

(d) Execution 4 (e) Execution 5

Figure 10: Map of emotions correlation

With the collection of this data it was possible to familiarise with the platform that was going to be used and to understand the best way to collect them. With this analysis of these, it was possible to have a better understanding of the type of data collected, how to extract them, how to join them and how to work with them.

1 The numbers correspond to the following emotions: 0-Anger; 1-Contempt; 2-Disgust; 3-Fear; 4-Happiness; 5-Neutral; 6-Sadness; 7-Surprise

5

ASSOCIATING EMOTIONS AND BPM WITH PERFORMANCE

This chapter describes the second study that was done. This consists of using the results obtained in 8 of the 9 executions performed by each respondent.

5.1 STUDY DESCRIPTION

The study population are children from 5 to 12 years old from the *Agrupamento de Escolas de Pedome, Famalicão*.

In total, data were collected from 97 children. Of these 97 children, 20 were in Pre-school, 38 in Elementary School and 49 in Middle School (Table 1). There were 16 children aged 5, 4 with 6 years old, with 8 years old there were 10 children and 21 children aged 9 years. At 10 years old there were 29, 7 children aged 11 and lastly 10 children aged 12 as shown in Figure 11.

Table 1: Total of children by age and school year

Age	School	Total
5	Jardim de Infância de Ruivães	9
6	Jardim de Infância de Ruivães	3
5	Jardim de Infância de S. Mateus	7
6	Jardim de Infância de S. Mateus	1
8	EBI de Pedome 1ºciclo - 3ºano	10
9	EBI de Pedome 1ºciclo - 3ºano	8
9	EBI de Pedome 1ºciclo - 4ºano	13
10	EBI de Pedome 1ºciclo - 4ºano	6
11	EBI de Pedome 1ºciclo - 4ºano	1
10	EBI de Pedome 2ºciclo - 5º ano	23
11	EBI de Pedome 2ºciclo - 5º ano	1
11	EBI de Pedome 2ºciclo - 6ºano	5
12	EBI de Pedome 2ºciclo - 6ºano	10

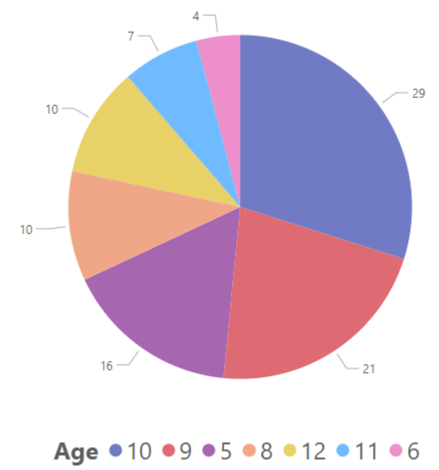


Figure 11: Total sample by age.

5.1.1 *Exercises used, images*

As already mentioned, this study uses only data relating to the first 8 experiences that each person performed. They are related to the recognition of emotions.

In these images, 4 faces are presented, representing different emotions, and a question, to which the person must indicate which of the faces represent the questioned emotion, as shown in Figure 12. The 4 five images displayed do not contain repeated faces, that is, twenty different faces are displayed. In the next 3 executions, the faces are repeated, that is, they belong to the group of the first 20 faces. Figure 12 and Figures 38 to 44 (in Appendix A) show the ordered executions.

Figure 12: Example of execution to recognise anger emotion

5.1.2 *Sample*

Overall data collected from 97 children, due to technical problems, in the end, data were obtained from at least one execution in 92 children. Of the 92, 23 children have data for a maximum of 8 runs and 74 have data for 9 executions, as represented in Figure 13.

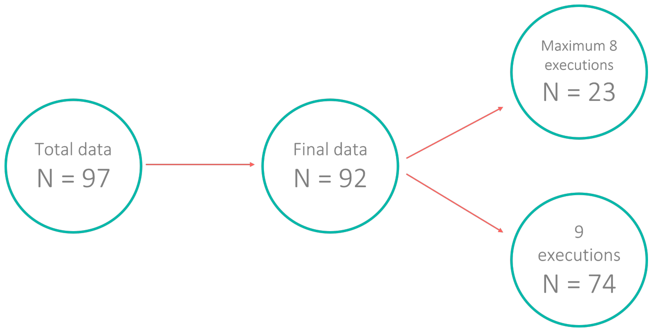


Figure 13: N of final data.

As in this study, only data from the first eight executions of each survey were used. In other words, only executions relating to the experience of emotions. For each of these experiments, there is the following number of runs, as shown in Figure 14:

- Exec. Anger: 84
- Exec. Happiness: 86
- Exec. Sadness: 90
- Exec. Fear: 86
- Exec. Surprise: 84

- Exec. Anger*: 90
- Exec. Fear*: 87
- Exec. Sadness*: 90

*Executions with repetition of images

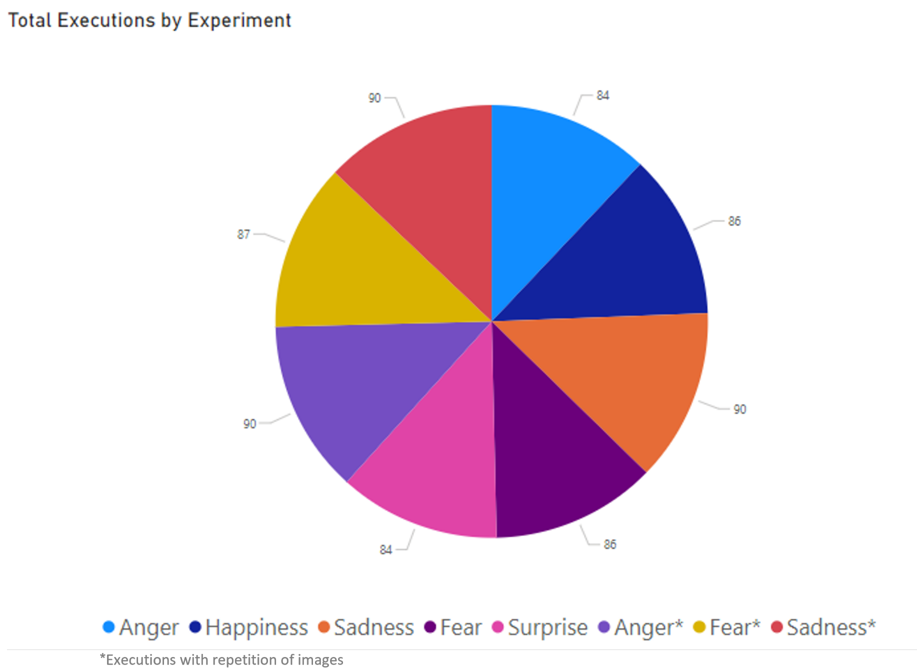


Figure 14: Total executions by experiment.

5.2 COLLECTED DATA

To start, it was decided to create some Python scripts, to merge relevant data from various sensors.

First, the files of each execution had to be transferred, in txt format, extracted from the oximeter software to JSON, as it is a more practical format to use and access information. Each new file has the name of the execution. These contain the information of BPM (Beats Per Minute) and SPO2 (Peripheral Oxygen Saturation) every second, as represented in Figure 15.

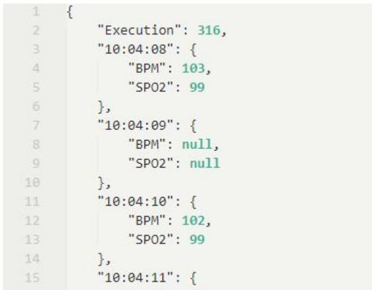


Figure 15: Excerpt of the file with the oximeter data relating to execution.

After, one file in CSV format was created, this file contains the information by zone for executions.

In this study, the CSV file contains the experience name, the execution id, the respondent id, the emotion id, the age, the age coming from Microsoft API, the number of points, the number of fixations, the average of fixations, the direction of movement, the two emotions that stand out the most, the value of those emotions, the zone, the emotion represented in that zone. This information is retrieved through the API used in the CNB platform. In the end, two new columns are added to these files, one with data relating to BPM and SPO2.

To create this file, the Python script was run, which automatically transforms the oximeter's txt files into JSON for all the executions. It also generates the CSV file with the appropriate information and merges the oximeter's information with the CSV. During the run of this script, the data of each execution coming from the CNB API, the primary data has some metrics already calculated, are saved in different files to avoid many API calls every time the script is executed.

This CSV file contains 3987 entries and an average of 6 entries per execution. This means there were found on average 6 emotions inside of the different zones.

5.2.1 *Dataset characterisation*

The final dataset is composed of the following 18 attributes:

- Experience name – **Nominal**
- The ID of the execution– **Integer**
- The person's ID – **Integer**
- The image ID – **Integer**
- The child's age – **Integer**
- Age by Emotion API - **Integer**
- Number of points - **Integer**
- Number of fixations - **Integer**
- Average of fixations - **Real**

Note!
A zone is a virtual mark of a certain place in the experiment.
The zones of each experiment are defined manually when entering the experiment on the platform. It is possible to access their values through the API provided by the platform and with these values it is possible to calculate if a point is inside a zone or not.

- Eye movement direction - **Nominal**
- Name of the emotion with the highest value given by the Face API - **Nominal**
- Value of emotion with the highest value given by the Face API - **Real**
- Name of the emotion with the second-highest value given by the Face API - **Nominal**
- Emotion value with the second-highest value given by the Face API - **Real**
- Zone name - **Nominal**
- The emotion that is represented by the zone - **Nominal**
- Beats per minute - **Nominal**
- Peripheral Oxygen Saturation - **Nominal**

5.2.2 *Some dataset statistics*

In this subsection, some metrics about the dataset that are relevant will be presented.

Regarding the attribute that represents the name of the experiment, the data is balanced. That is, each experiment has more or less the same amount of entries in the dataset. Figure 16 shows how much data each experiment has.

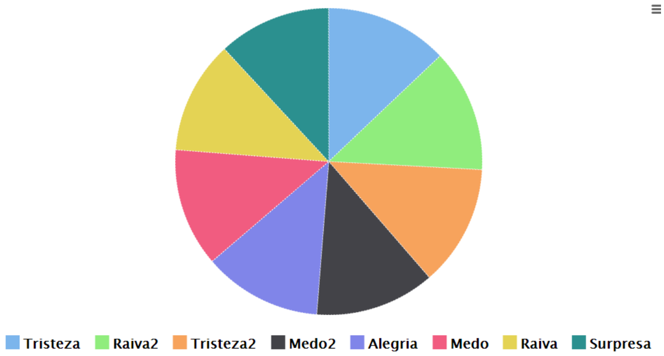


Figure 16: Distribution of experiences in the dataset.

In terms of age in the dataset, the average is 8,93, with 9 as the median. Its variance is 4,385 and its deviation is 2,094. It should be noted that there is more than one entry for each child in the dataset, with the average age of children in this study being 8,84. Through the bar graph represented in Figure 17, it can be seen that there is no data from 7-year-old children.

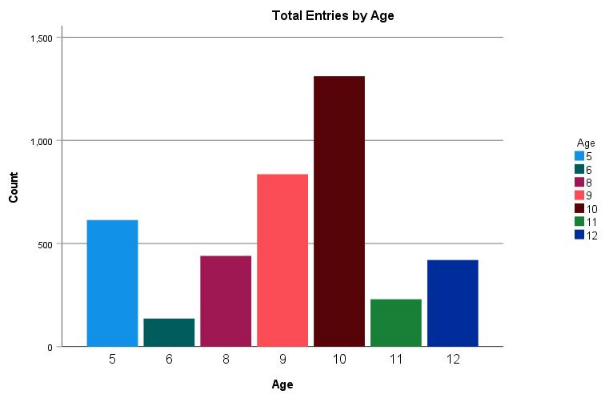


Figure 17: Total entries by age.

Regarding the emotions detected, along with each experience made to children, through the Microsoft emotions API, it was possible to see that the neutral was the emotion with the highest value, which stood out, with 3735 entries, over the executions following of happiness emotion, with 222. As for the emotion with the second-highest value, it was the emotion of sadness that stood out, with 1960 entries, followed by happiness with 673 entries.

5.3 APPLIED TECHNIQUES

To discover new knowledge, it was decided to use RapidMiner software due to its great availability of resources and the fact that its interface is quite intuitive. This section describes data preprocessing and how data mining techniques are implemented.

5.3.1 *Association Rules*

It starts by preprocessing the created dataset. In this, it was decided to begin with detecting and removing the outliers in each dataset (Figure 18). The detection of outliers serves to find instances that have a marked deviation relative to others. These instances if are not detected can influence the results of the modelling process.

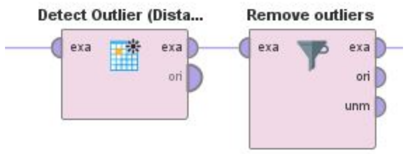


Figure 18: Detect outliers and filter operators.

Then, the file is filtered so that it does not include instances that contain, in the "BPM" attribute, the values "Sem Resultados". With these changes, the file has 3758 instances.

After, the most relevant attributes are selected. These are: "Age", "AVG_Fixation", "BPM", "Emotion_Max1_Name", "Emotion_Max2_Name", "Emotions", "Movement". After selecting the attributes, the values were normalised and, finally, the numerical values are passed to polynomials and from nominal to binomials, once the modelling process with association rules was started.

After preparing the data to create association rules, the operator "FP-Growth" and the "Create Association Rules" were used, as shown in Figure 19 .

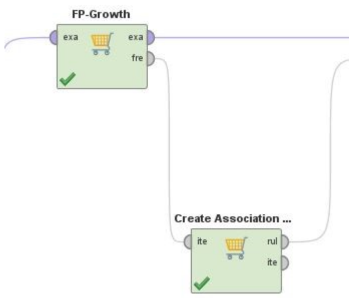


Figure 19: "FP-Growth" and "Create Association Rules" operators.

The following scenarios were created to try to obtain the rules:

- **S1**: Predefined values by RapidMiner. That is, minimum support = 0,95 and minimum confidence = 0,8
- **S2**: Minimum support = 0,5 and minimum confidence = 0,8
- **S3**: Minimum support = 0,2 and minimum confidence = 0,5

5.3.2 *Induction Rules*

For this technique, the beginning of data processing was identical to that of the previous subsection. The outliers and "Sem Resultado" values have been removed, but different attributes were selected.

This technique was used to try to establish relationships between bpm and the emotions that respondents were looking for. It was also applied to find a relationship with bpm when looking at a certain area.

Next, to create induction rules, it is necessary to use the "Set Role" operator to assign which attribute is a "Label", that is, which attribute is the "class" or the "target variable". Lastly, the operator "Rule Induction", with Predefined values by RapidMiner was used, as shown in Figure 20.

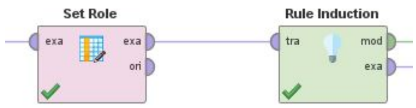


Figure 20: "Set Role" and "Rule Induction" operators.

With this technique the following 2 scenarios were created:

- **S4**: Only the attributes "BPM" and "Experiment" were used. The role "Label" is assigned to the "Experiment".
- **S5**: Only the attributes "BPM" and "Emotions" were used. The role "Label" is assigned to the "Emotions".

5.4 RESULTS

5.4.1 *Association Rules*

Using the scenarios described in 5.3.1, in the first scenario (**S1**), with the values predefined by Rapidminer, no rule was obtained. In **S2**, it was possible to obtain a rule in which the premise is "Emotion_Max2_Name = Sadness", the conclusion is "Emotion_Max1_Name = Neutral". This rule, despite having a very high confidence value, almost 1, the support value 0,503 is a little low. Using the last scenario, 8 rules are obtained. These rules have very low support values, despite good confidence values.

As the most relevant rules always result in conclusions related to the highest emotion value, it was decided not to use this attribute ("Emotion_Max1_Name"), as the emotion that stood out the most during the executions was neutral, which may be influence other types of conclusions.

Despite this change, no rules were found that lead to thinking of another strategy and use induction rules.

5.4.2 *Induction Rules*

In this technique, using the scenario **S4**, described in section 5.3.2, 203 rules were obtained. These rules were saved in a txt file and then passed to a CSV file where the a BPM value matches the name of an experiment. This was possible, because all the rules matched a BPM value to the name of the experiment (Example of a rule: "if BPM = 115.0 then Raiva").

With this file, the values were grouped by name of the experiment where it was possible to calculate the average value, the highest value and the minimum value of the bpm. The results obtained were: in the experiment where they have to find the emotion of happiness they have an average of heartbeats higher than the others and where they have to find the emotion of surprise they have an average of lower value. The experience where it is necessary to find the expression that matches the emotion of happiness has the highest maximum BPM value, and the experience where it has to determine the face that matches the emotion of surprise got 98.5, which corresponds to the lowest maximum value. Of the minimum BPM value, the experience where it is suppose to find the expression that represents the emotion of sadness has the greatest value and the experience where it is suppose to detect the emotion of anger has the least value. The result values can be seen in table 2.

Table 2: Results for S4 of the induction rules

	BPM Average	BPM Max	BPM Min
Anger	80.619	119	37
Happiness	98.615	136	41
Sadness	87.810	116	49
Fear	83.915	114	41
Surprise	69.500	98.5	45

Using the **S5** scenario, also described in section 5.3.2, 191 rules were obtained. As in the previous scenario, these rules were saved in a txt file and move to a CSV file where the BPM value corresponds to the emotion represented by the zone.

Through this file, the same values as in scenario **S4** were calculated. The results obtained were: in the zone that represents the emotion of disgust it has an average of bpm much lower than the others and in the zone that represents the emotion of happiness it has a higher average value. If the zones that represent emotions that do not correspond to the emotions that have to be indicated in the experiences are removed, the zone that represents the surprise emotion has the lowest average value, although higher than in the previous scenario. Regarding the highest value of bpm, the zone that corresponds to the emotion of sadness is where the highest value is found. The lowest value is found in the area that corresponds to the emotion of disgust. As for the lowest value of beats per minute, the zone that corresponds to the anger emotion is where the lowest value is found and, the area that corresponds to the surprise emotion is where the highest value is found. Table 3 shows the results of this scenario.

Table 3: Results for S5 of the induction rules

	BPM Average	BPM Max	BPM Min
Anger	84.756	117	37
Contempt	70.750	117	38
Disgust	52.167	71	41
Fear	83.725	113	42
Happiness	92.579	128	41
Sadness	90.020	136	44
Surprise	79.950	115	45

In this Chapter it can be seen that the association rules did not bring great advantages, because although some of these rules have high confidence values, the support is low. As for the induction rules, these show that happiness generates a higher BPM, while Surprise generates lower values.

6

ASSOCIATING BPM AND PERFORMANCE

In this chapter, the third study is described. This one consists of applying the same process as the previous study, using the results obtained from the last execution, performed by each respondent.

6.1 STUDY DESCRIPTION

In this study, the same population was used as in study 2. In total there are 97 children from 5 to 12 years old from the *Agrupamento de Escolas de Pedome, Famalicão*. The population is described in Chapter 5, in the section 5.1.

6.1.1 *Exercises used, images*

For this study, data relating to the last exercise that each person performed is used. These are related to two BANC quick queries naming tests. In these quick naming tests, children are asked to name as quickly as possible if they encounter constant visual stimuli that are repeated in 5 random sequences of 10 elements. Depending on the child's age, a different test is applied, for children from 5 to 6 years old the quick naming of colours test, as shown in Figure 45 (in Appendix A), is applied and for children from 7 to 15 years old, the quick naming of shapes and colours test, as shown in Figure 46 (in Appendix A), is applied. However, the quick naming of colours test requires the child to name stimuli belonging to the same 5 colours category, while the quick naming of shapes and colours test requires the child to name stimuli that belong to 2 semantic categories are geometric shapes and colours. This last one requires, of course, greater complexity.

6.1.2 *Sample*

As in the previous study, some executions had some technical problems. Of the total data from 97 children that could be used for these experiments, it was viable to use data from 88 executions. For quick naming of colours of the 20 children aged to take this test, it was only possible to use 17 of them. Of the 77 children who took the shapes and colours test, it was possible to use data from 71 tests.

6.2 COLLECTED DATA

As previously described in Section 5.2, it was necessary to convert the data related to the oximeter, which are in .txt, to JSON format for the executions used for this study. At the end of this process, each execution has a file containing the BPM and SPO2 information. As in the previous study, the Python script was used, which automatically performs the conversion described above, and which creates the file in CSV format that contains the information by area relating to the quick naming tests. After, it merges the data from the oximeter with the information from the CSV file. The file used for this study contains the experiment name, the execution id, the respondent id, the emotion id, the age, the age coming from the Microsoft API, the number of points, number of fixations, average fixations, the direction of movement, the two emotions that stand out the most, the value of those emotions, the zone, colour and shape represented in that zone, type of error, BPM, SPO2.

6.2.1 *Dataset characterisation*

The final dataset is composed of the following 18 attributes:

- Experience name – **Nominal**
- The ID of the execution– **Integer**
- The person's ID – **Integer**
- The image ID – **Integer**
- The child's age – **Integer**
- Age by Emotion API - **Integer**
- Number of points - **Integer**
- Number of fixations - **Integer**
- Average of fixations - **Real**
- Eye movement direction - **Nominal**
- Name of the emotion with the highest value given by the API - **Nominal**

- Value of emotion with the highest value given by the API - **Real**
- Name of the emotion with the second-highest value given by the API - **Nominal**
- Emotion value with the second-highest value given by the API - **Real**
- Zone* name - **Nominal**
- Colour or Shape and Colour represented by the zone - **Nominal**
- Type of error - **Nominal**
- Beats per minute - **Nominal**
- Peripheral Oxygen Saturation - **Nominal**

  *Review the meaning of zone, in the note, in subsection 5.2.1 of the previous chapter.

6.2.2 *Some dataset statistics*

The dataset under study contains 19 attributes and some are not relevant to the study, such as identification attributes, so this subsection will only present some metrics of some attributes.

Regarding the age attribute, this has an average of 9,19, a standard deviation of 1,83 and a median of 10. In the bar graph, represented in Figure 21, it is possible to see the distribution of dataset entries by age.

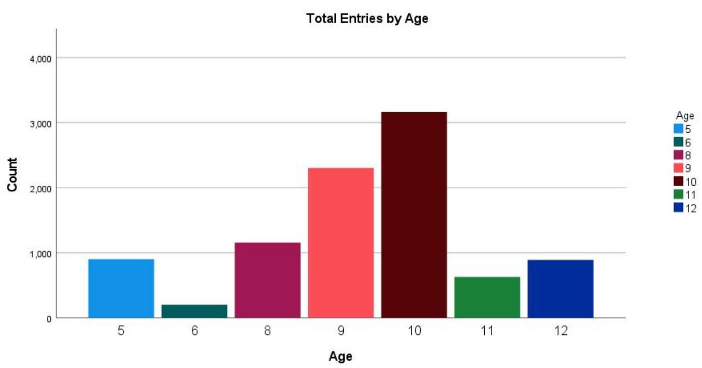
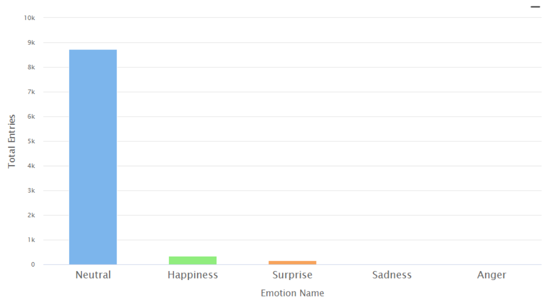
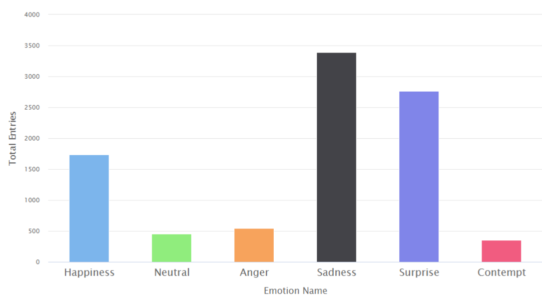


Figure 21: Total entries by age.

As in the previous study, the emotion with the highest value, which has the most inputs is neutral, with 8728 instances, and then happiness with 347 entries, these values can be seen in Figure 22(a) . Figure 22(b) shows that the emotion with the second highest value, which has more entries in the dataset is sadness with 3393 entries, and then surprise with 2768 records.



(a) Total emotions with the highest value



(b) Total emotions with the second highest value

Figure 22: Graphs of the amount of emotions expressed.

6.3 APPLIED TECHNIQUES

As in the previous study in section 5.3, this section describes data preprocessing and how data mining techniques are implemented for this new dataset. RapidMiner software was also used. In this section, the association rules and induction rules will be presented as in the previous study.

6.3.1 *Association Rules*

Data preprocessing, of the created dataset, was started by detecting and removing outliers. But as the dataset have almost 10000 rows, the search for outliers takes a long time and this consumes a lot of memory on the machine where the software is running, the RapidMiner ends up going down, which makes you have to start processing again. So there was 2 options, do without detecting outliers or by calculating the percentiles of attributes to see which entries can have outliers and remove them manually. The results will be displayed without removing the outliers.

After, the 'BPM' attribute was filtered to not contain the value "Sem Resultados". Next, it was selected the following attributes:r "Age", "AVG_Fixation", "BPM", "Emotion_Max1_Name", "Emotion_Max2_Name", "Zone". Then, the values were normalised and, finally, the numerical values are passed to polynomials and from nominal to binomials, once the modelling process with association rules was started.

Like in the previous study, to create association rules, the operator "FP-Growth" and the "Create Association Rules" were used.

For the dataset without removing outliers, to try to obtain the rules, the following scenarios were created :

- **S1**: Predefined values by RapidMiner. That is, minimum support = 0,9 and minimum confidence = 0,8
- **S2**: Minimum support = 0,5 and minimum confidence = 0,8
- **S3**: Minimum support = 0,2 and minimum confidence = 0,5

6.3.2 *Induction Rules*

In this technique, a similar data processing was used. This technique uses also the dataset without removing the outliers. The "Sem Resultado" values were also removed. The difference in preprocessing is in the selection of attributes to be used. For this, only two attributes are used "BPM", "Colour or Shape and Colour". As already described, in the previous study, to create the induction rules it is necessary to define a label role to one of the attributes used. For creation rules, the operator, "Induction Rule" is used, with the RapidMiner default values.

Through this technique, an attempt is made to find some relationship between the heartbeat and the colour, or shape and colour, that respondents have to name.

With this technique the following 2 scenarios were created:

- **S7**: Using both attributes, but using only the values referring to the naming of shape and colours. The role "Label" is assigned to the "Colour or Shape and Colour" .
- **S8**: Using both attributes, but using only the values referring to the naming colours. The role "Label" is assigned to the "Colour or Shape and Colour" .

6.4 RESULTS

6.4.1 *Association Rules*

In scenario (**S1**), described in 6.3.1, it was obtained 5 rules, as seen in Figure 23. This rules have a confidence high, above 0.95, although a support below 0.4. The rule with the highest confidence value (1) have the highest support value (0.376). Theses rule have the premise "Emotion_Max2_Name = Sadness" and the conclusion is "Emotion_Max1_Name = Neutral".

In the other two scenarios, as seen in the other study x, it can be noted that there is an increase in rules, 12 rules were obtained for S2 and 19 rules for S3. Despite these new rules, the support value of these rules is lower although there may be higher confidence values.

No.	Premises	Conclusion	Support	Confidence
1	Age = 0.571	Emotion_Max1_Name = Neutral	0.246	0.952
2	Age = 0.714	Emotion_Max1_Name = Neutral	0.338	0.956
3	AVG_Fixation = 0	Emotion_Max1_Name = Neutral	0.334	0.964
4	Emotion_Max2_Name = Surprise	Emotion_Max1_Name = Neutral	0.305	0.996
5	Emotion_Max2_Name = Sadness	Emotion_Max1_Name = Neutral	0.376	1

Figure 23: Rules obtained in scenario 1.

6.4.2 *Induction Rules*

Using the values of naming shapes and colours, scenario 1 (**S7**) 199 rules were found. In scenario **S8**, using the colour naming values, 121 rules were generated. Those rules were saved in separate files, in txt format. Then they were passed to files in CSV format, one contained the shape and colour and "BPM" and the other the colour and "BPM".

Using a python script, the average, the highest value and the lowest value by shape and colour (in scenario 7) or, by colour (in scenario 8) was calculated.

For S7, the shape and colour that obtained the highest average was the black rectangle, and the one that obtained the lowest average was the black triangle. The highest BPM value (139) occurs in the black rectangle and red rectangle, the lowest value (58) occurs in the black square. The total result obtained can be seen in table 4.

For S8, the colour that obtained the highest average was the green, and the one that obtained the lowest average was the red. The highest BPM value (123) occurs in the colour blue, the lowest value (44) occurs in the colour red. The total result obtained can be seen in table 5.

Table 4: Results for the scenario 7

Shape and colour	BPM Average	BPM Max	BPM Min
YELLOW CIRCLE	84.83333	122	59
BLACK CIRCLE	101.7143	131	59
GREEN CIRCLE	80.1875	113.5	61
Red CIRCLE	95.66667	126	61
YELLOW SQUARE	92.65789	135	64.5
BLACK SQUARE	87.83333	125	58
BLACK RECTANGLE	102.1591	139	81
GREEN RECTANGLE	93.82353	127	63
RED RECTANGLE	96.14583	139	60
YELLOW TRIANGLE	99.15	124	68
BLACK TRIANGLE	79	100	60.5
GREEN TRIANGLE	92.66129	119	62.5

Table 5: Results for the scenario 8

Colours	BPM Average	BPM Max	BPM Min
YELLOW	97.39286	118	45.5
BLUE	96.45455	123	46
BLACK	98.73529	119	44.5
GREEN	101.1	121.5	81
RED	95.97561	121	44

For the same reason as in the previous chapter, association rules were not relevant.The induction rules show that there are no big variations in BPM by the zone you are looking at.

7

CORRELATING MEMORY AND ATTENTION WITH PERFORMANCE - 1^{st} EXPERIMENT

In this chapter, a new study that began to develop after the results of other studies did not generate new knowledge that could aid in the diagnosis will be described. This study began as an individual study of some respondents, based on data from new tests performed and the addition of new variables. In terms of the population, there was an increase, as it was possible to perform more tests on different children from the *Colégio Menino Deus*.

7.1 STUDY DESCRIPTION

Like in other studies, the population are children from 5 to 12 years old. In total, there are 152 children in this study. 97 children belong to *Agrupamento de Escolas de Pedome* and 55 children belong to *Colégio Menino Deus*. Of the children who participated in this study, 34 are between 5 and 6 years old, 39 are between 7 and 8, 29 are 9 years old and 35 are 10 years old. Finally, there are 17 children aged between 11 and 12 years old.

Table 6: Total of children by age and school year

Age	School	Total
5	Jardim de Infância de Ruivães	9
5	Jardim de Infância de S. Mateus	7
6	Jardim de Infância de Ruivães	3
6	Jardim de Infância de S. Mateus	1
6	Colégio Menino Deus - 1ºano	14
7	Colégio Menino Deus - 1ºano	12
7	Colégio Menino Deus - 2ºano	4
8	EBI de Pedome 1ºciclo - 3ºano	10
8	Colégio Menino Deus - 2ºano	4
8	Colégio Menino Deus - 3ºano	9
9	EBI de Pedome 1ºciclo - 3ºano	8

Age	School	Total
9	EBI de Pedome 1ºciclo - 4ºano	13
9	Colégio Menino Deus - 3ºano	3
9	Colégio Menino Deus - 4ºano	3
10	EBI de Pedome 1ºciclo - 4ºano	6
10	EBI de Pedome 2ºciclo - 5º ano	23
10	Colégio Menino Deus - 3ºano	1
10	Colégio Menino Deus - 4ºano	5
11	EBI de Pedome 1ºciclo - 4ºano	1
11	EBI de Pedome 2ºciclo - 5º ano	1
11	EBI de Pedome 2ºciclo - 6ºano	5
12	EBI de Pedome 2ºciclo - 6ºano	10

7.1.1 *Exercises used, images*

For this study, 2 diagnostic tests were used. The first test,represented in Figure 47 (in Appendix A), aims to evaluate the orientation attention that measures the ability to concentrate, the power of achievement and the resistance to tiredness and thus try to detect possible attention deficits. This test lasts 10 minutes and consists of children finding referred symbols by selecting from a set of randomly placed stimuli. The second test, represented in Figures 48 and 49 (in Appendix A),is applied depending on the child's age. For children between 6 and 7 years old, a test that measures the ability to associate geometric shapes to symbols is applied if the child is between 8 and 16 years old, a test that measures the ability to associate numbers to symbols is applied. These tests also measure the capability to correctly memorise these associations to perform the task as quickly as possible. Also, allow it to assess the ability of automated "mechanical" learning. The result of the tests is given through a percentile from zero to 20. The higher the percentile, the better is the memory capacity or attention capacity.

The quick naming of colours test and the quick naming of shapes and colours described in a study of 3 were also used. The result obtained in this test, such as the number of errors and omissions, and the time it took to take the test, will be used to make comparisons with the outcome of the diagnostic tests mentioned above.

7.1.2 *Sample*

Of the total of 152 tests performed in this study, due to technical failures, only 149 were used. Of these 149, 36 took the quick naming of colours test (in some cases, 7-year-old children took this test) and 113 took the quick naming of shapes and colours test. Initially, the memory test was not applied and, therefore, many of the executions of the rapid naming of colours test will not be used as you will see in section 7.3.

7.2 COLLECTED DATA

After the results of previous studies, there was a need to create new datasets that would allow the individual to analyse the respondent.

Therefore, a script (Script1) was created using the data that can be taken from each patient through the API, which provides data regarding the points and fixations of an execution and which already provides a few meters calculated as a recognition of the emotion. This script saves in a file ("Info_ExecsTotal.json") the data, such as the coordinates of the points, the duration of the fixations, the zone (and sub-zones, if any), among others. Also, it saves in another file ("Emotions_Execs.json") the data related to the emotions of each execution. Both files are in .json format.

From the information, of each execution that is stored in the files, different datasets were constructed, using more different scripts in Python.

For this study, two files, File1 and File2, were created (in .xlsx format) for each execution. The File1 contains information regarding all the points that occurred during the test and the File2 contains only data relating to the fixations that the respondent made during the test. The information from these two files involved calculating new metrics such as distance, time interval and angle between points and whether a line break occurred. There was also a review of the calculation of the type of direction of movement, which in this study now has two values, horizontal movement(from left to right, or right to left), represented in Figure 24, and vertical movement (from top to bottom, or from bottom to top). The Script2, through the "Info_ExecsTotal.json" file, will obtain the information of all executions related to the test used in this study for the creation of these files.

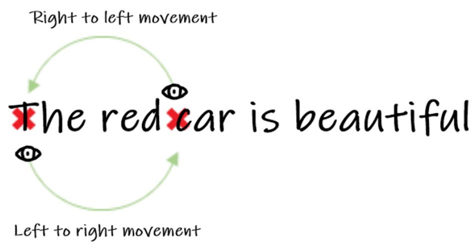


Figure 24: Types of horizontal movement

To calculate the distance between points, represented by the line segment (d_{AB}), was applied the Pythagorean theorem since the line segment is the hypotenuse of the triangle formed. Formula 1 represents the distance between points.

$$d_{AB} = \sqrt{(x_B - x_A)^2 + (y_B - y_A)^2} \tag{1}$$

The calculation of the time interval between points is given by 2 where tB is the device timestamp of point B and tA is the device timestamp of point A.

$$\Delta t = tB - tA \tag{2}$$

To calculate the angle between two points, it is necessary to know the distance between the eye and the screen, so the respondents is always place at a distance of 66 cm. Figure 25 shows a schema of the representation of the angle to be calculated and this is equal to 2θ. Knowing that $\sin = \frac{opposite}{hypotenuse}$, being the opposite equal to half d_{AB} and the hypotenuse equal to the distance between the eye and the screen, so theta is given by the following formula:

$$\Theta = \sin^{-1}\left(\frac{opposite}{hypotenuse}\right) \tag{3}$$

The type of movement is calculated from the position of the points. For horizontal movement it uses the values of the X axis and for the vertical movement the values of the Y axis. The horizontal movement from left to right occurs when $x_B >= x_A$ and right-to-left movement happens when $x_B < x_A$. The vertical movement from top to bottom occurs when $y_B <= y_A$ and bottom-up movement happens when $y_B > y_A$.

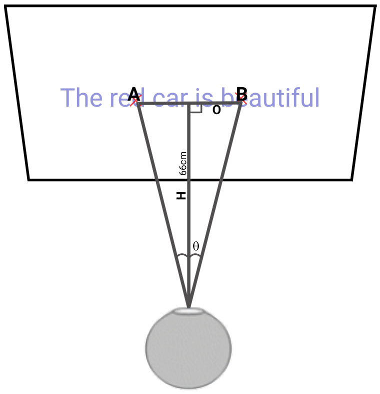


Figure 25: Representation of the angle between two points

To find out if a line change occurred between two points, it was decided to use the distance, the angle value and the type of movement between these points. We consider that there is a line break when the movement occurs from right to left and from top to bottom, the distance between points must be greater than 400 and the angle must be greater than 12°. If all conditions are satisfied, a line break has occurred and the value 1 is assigned to that point.

In the end, these files are made up of the position where the points occurred, the distance between the points, the point timestamp (time the point was saved), the device timestamp of the point (value provided by the eye tracker), the time interval between points, duration of a fix (0 if a point), the horizontal movement, the vertical movement, the angle, the zone and line/column.

The Script3 was used that calculates different metrics and joins metrics already saved in a previously created file. This script calculates the total of points and fixations through the length of the lists generated through the use of a filter (to obtain lists with only points and lists with just fixations). The total of regressions is calculated by adding the horizontal movements that occur from the right to the left between fixations and the percentage of regressions is calculated from the $\frac{totalregressions}{totalfixations} * 100$. The total line-breaks are calculated from the sum of the "line break" column, the test duration is calculated from the formula 4.

$$\Delta t = tf - ts \tag{4}$$

where tf = final timestamp and ts = start timestamp

The Script3, also, uses a file (in .json), which contains information regarding the errors and omissions of each execution, to obtain the total number of errors, total number of omissions and the sum of both. It also uses files (in .xlsx) that contain data about the results of memory and attention deficit tests.

Two data sets were also created, for each execution. One of these datasets contain the position of each point and its device timestamp, the other contains the position of each fixation and its device timestamp.

7.2.1 *Dataset characterisation*

In this study, the name of attributes was written in Portuguese, so that there is no confusion about their translation.

Dataset 1 - Set of data created regarding the information of the points during each execution.

- **Ordem dos pontos** - Integer: order in which the point/fixation occurred;
- **Distância entre pontos/fixações** - Real
- **Timestamp** - Time: time at which the point occurred;
- **Timestamp do eye tracker** - Real: value assigned to the time the point occurred, given by the eye tracker
- **Intervalo de tempo entre pontos/fixações** - Real: time interval that occurred between two points or two fixations;
- **Duração** - Real: duration of a fixation, 0 if is a point;
- **Movimento Horizontal** - Nominal: whether the eye movement is right to left("DE") or left to right("ED");
- **Movimento Vertical** - Nominal: whether the eye movement is top-down ("CB") or bottom-up ("BC");
- **Ângulo** - Real: angle between points;
- **Zona** - Nominal: virtual representation for where the point/fixation;

- **Linha/Coluna** - Nominal: row and column where the point is located on the experiment, given through the zone;
- **Mudança de linha** - Integer: if there was a change to the next line;

Dataset 2 - File with data relating to all executions.

- **Execução** - Integer: execution identifier;
- **Experimento** - Integer: experiment identifier;
- **ID da Pessoa** - Integer: person identifier;
- **Idade** - Integer: respondent's age;
- **Wisc** - Integer: represent the percentile obtained in the memory test;
- **Cancelamento** - Integer: represent the percentile obtained in the attention test;
- **NomRap** - Integer: represent the percentile obtained in rapid naming test
- **Resultado** - Nominal: is the junction of the result of the attention deficit test with the result of the memory deficit;
- **Total de Pontos** - Integer: total of points given in the quick naming test;
- **Total de Fixações** - Integer: total of fixations given in the quick naming test;
- **Total de Regressões** - Integer: total of regressions given in the quick naming test
- **% de Regressões** - Real: percentage of regressions in the quick naming test;
- **Total de Mudanças de Linha** - Integer: total of line breaks given in the quick naming test;
- **Total de Tempo** - Real: quick naming test run-time;
- **Erros** - Integer: total of errors given in the quick naming test;
- **Omissões** - Integer: total of omissions given in the quick naming test;
- **Total E+O** - Integer: total of errors and omissions given in the quick naming test.

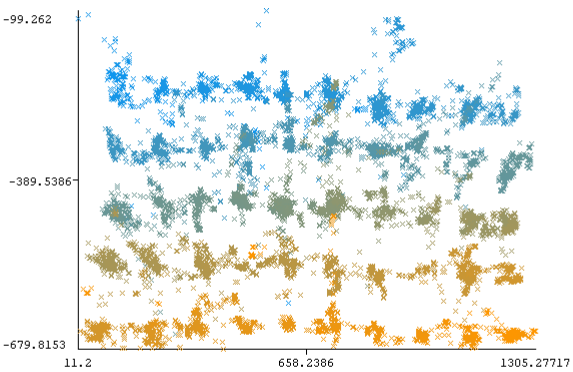
Dataset 3 - Set of files, for each execution, with the position of the points and the timestamp.

- **X** - Real: position of point on the x-axis;
- **Y** - Real; position of point on the y-axis;
- **Timestamp do eye tracker** - Real: value assigned to the time the point occurred, given by the eye tracker;

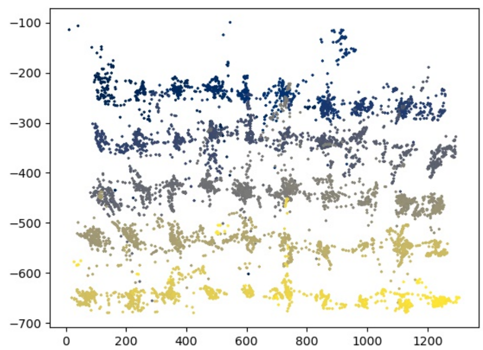
7.3 DESCRIPTION

This study involved an initial survey of some individual children to see if there were differences in the metrics, of the files with the structure of the data set 1 of subsection 7.2.1, that were relevant between respondents with memory and attention deficit and those with good capability of memory and attention. With this individual analysis, through a comparison of 5 cases of respondents with memory and attention deficit and the same number for cases without memory and attention deficit, it was possible to notice that individuals with some deficit present, on average, a greater number of fixations and regressions, they also present longer time for test execution.

After this individual analysis, it was necessary to generate graphs that represent the points, in order to better understand how the points and fixations happen throughout the test. To make these graphics it was used the Weka software because with this it was possible to obtain sharper graphics than using Python's *matplotlib* library. It was tried to use Weka modules in python, but the graph produced is identical to the one generated by building a graph with the *matplotlib* library. For the construction of the graphics, files with the structure of data set 3 were used (described in subsection 7.2.1). Figure 26(a) shows the graph generated through the Weka software and Figure 26(b) shows the graph generated through a Python script. Therefore, for this analysis, it was chosen to use the graphics taken from Weka.



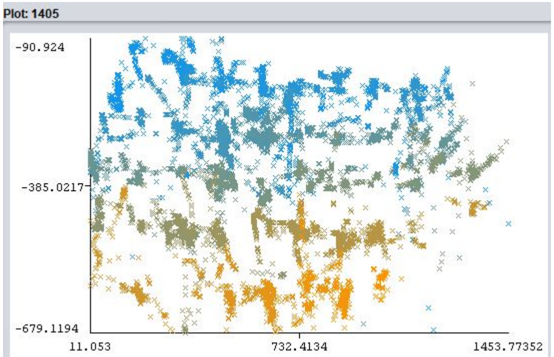
(a) Graphic extracted from Weka software



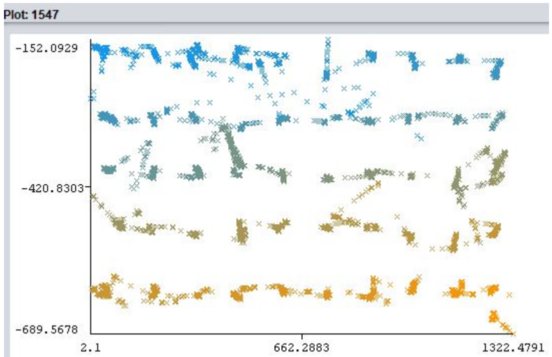
(b) Graphic extracted from Python

Figure 26: Graphs of points from a run extracted via (a) Weka, and (b) Python

Through the graphs of the 10 respondents analysed above, it was possible to notice that individuals with memory and attention deficit tend to get lost along the 5 lines present in the rapid naming test [(as shown in Figure 27(a)] , that is, there is no well-defined line while the children with good memory and attention capacity had graphics [as shown in Figure 27(b)] where it was possible to see the definition of the 5 lines.



(a) Graphic of a child with memory and attention deficit



(b) Graphic of a child with good capacity of memory and attention

Figure 27: Difference between the naming test graph between children with good and poor attention and memory capacity

With this, it was decided to calculate some new metrics through the files that have the structure represented by the dataset 2. These metrics are based on the average of points, fixations, duration time, total regressions, percentage of regressions and total errors. These new metrics were applied to statistical methods to see if there was a correlation between them and the test results.

With the data from each test that are in this dataset, it is verified if there is a correlation between the result of the memory test and the attention test with the other metrics. For this study, as for the previous studies, the RapidMiner software was used. As one test was used for children aged 5 to 6 years and another test was used for children aged 7 and up, the analysis of these data was also separated by test. Therefore, there are the following scenarios:

- **S9** - Only the data from the quick naming of colour.
- **S10** - Only the data from the quick naming of shapes and colours.
- **S11** - Both tests.

In scenario S9, it was necessary to make a filter to select only children who took both tests, so the attributes "Wisc" and "Cancelamento" must be greater than or equal to 0. A filter that only selects the identifier of the quick naming of colours proof has also been added. With these filters, our dataset had an n=15. Afterwards, the attributes that would enter the correlation matrix were selected, which were as follows:

To obtain the correlation matrix, the operator “Correlation Matrix” is added (Figure 28).

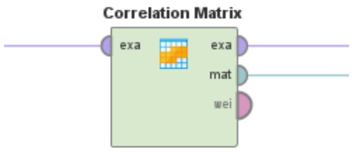


Figure 28: Correlation Matrix operator.

For scenario S10 the same process is used, the only change is in the filter that selects the proof identifier, which was changed to the proof identifier of the quick naming of shapes and colours, getting an n= 107. For scenario S11, it was removed the filter for the test identifier. This scenario gets an n= 122.

As with RapidMiner, it was not possible to see whether the data was statistically significant, it was chosen to use a statistical program called SPSS. As for RapidMiner, in this statistical software the following 3 scenarios were used:

- **S12** - Only the data from the quick naming of colour.
- **S13** - Only the data from the quick naming of shapes and colours.
- **S14** - Both tests.

For the construction of these scenarios, the dataset 2 was used. To obtain the different scenarios, it was selected the cases using the data tab, as shown in Figure 29.

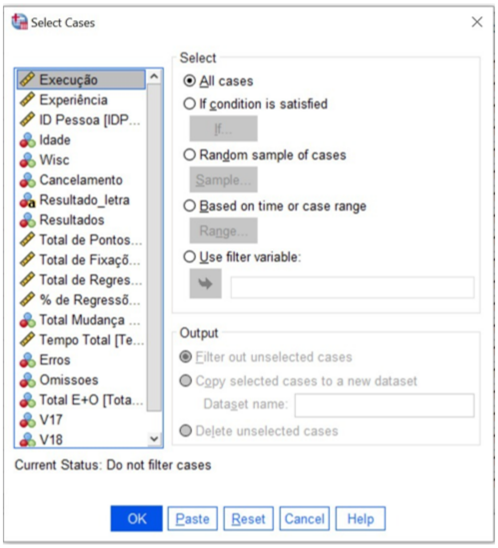


Figure 29: Selected Cases in SPSS

Then it is important to see if the attributes follow the normality, for this, it is necessary to do the Shapiro-Wilk test if n is less than 50 or the Kolmogorov-Smirnov test if n is greater than 50. Figure 30 shows the application of the two normality tests applied to the dataset used in scenario **S12**. If the significance is less than 0,05 the attribute does not follow normality, if is greater than 0,05 the attribute follows a normal distribution. After checking which attributes follow the normal distribution, the correlation matrix is created. If all attributes follow a normal distribution, then Pearson's correlation is used. If one of the attributes does not follow a normal distribution then Spearman's ρ is used. The attributes used in these scenarios were the same as those used in RapidMiner.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Wisc	0.188	15	0.159	0.905	15	0.113
Cancelamento	0.235	15	0.025	0.843	15	0.014
NomRapP	0.247	15	0.014	0.897	15	0.085
Total de Pontos	0.144	15	.200*	0.904	15	0.111
Total de Fixações	0.183	15	0.188	0.941	15	0.398
% de Regressões	0.139	15	.200*	0.968	15	0.826
Tempo Total	0.230	15	0.031	0.808	15	0.005
Total E+O	0.297	15	0.001	0.759	15	0.001

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Figure 30: Tests of Normality

7.4 RESULTS

The results obtained through the RapidMiner software, not forgetting that one wants to see the correlation between the test results and the other attributes, show that in relation to scenario **S9** (shown in Figure 31) the memory test has a negative correlation (review definition in section 4.3), below -0,50 with the number of fixations and the percentage of regressions, this means that the higher the percentile of the memory test, the smaller the number of fixations and the number of regressions. There is also a positive correlation, above 0,65, which shows that the better the result of the quick naming test, the better is the result of the memory test. Regarding the attention test, there are two stronger negative correlations, (below -0,60) between total time and total errors and omissions. This means that people with less attention deficit tend to perform tests faster and with fewer errors and omissions.

Attributes	Wisc	Cancelamento	NomRa...	Total de Pontos	Total de Fixações	% de Regressões	Tempo Total	Total E+O
Wisc	1	0.272	0.681	-0.125	-0.561	-0.609	-0.361	0.050
Cancelamento	0.272	1	0.196	-0.355	-0.322	-0.373	-0.610	-0.759
NomRapP	0.681	0.196	1	-0.564	-0.691	-0.592	-0.699	0.220
Total de Pontos	-0.125	-0.355	-0.564	1	0.316	0.195	0.839	0.089
Total de Fixações	-0.561	-0.322	-0.691	0.316	1	0.893	0.599	0.149
% de Regressões	-0.609	-0.373	-0.592	0.195	0.893	1	0.508	0.172
Tempo Total	-0.361	-0.610	-0.699	0.839	0.599	0.508	1	0.240
Total E+O	0.050	-0.759	0.220	0.089	0.149	0.172	0.240	1

Figure 31: Correlation Matrix obtained in scenario **S9**.

For the **S10** scenario, the correlations, with the attribute that represent the test for the detection of memory deficit and with the attribute that represent the test for the detection of attention deficit, show weaker values than the **S9** scenario, shown in Figure 32 . The most relevant correlations in this scenario are with the attribute that represents the duration of the test and the attribute that represents the result of the quick naming test. The correlation between the result of the memory test and the rapid naming test is positive and the correlation between the total time and the memory test is negative. Regarding the correlations with the attention deficit detection test, there is no correlation above 0,45 and below -0,45. For scenario **S11** the same happened as for scenario **S10**.

Attributes	Wisc	Cancelamento	NomRapP	Total de Pontos	Total de Fixações	% de Regressões	Tempo To...	Total E+O
Wisc	1	0.216	0.476	-0.241	-0.251	-0.371	-0.482	-0.268
Cancelamento	0.216	1	0.324	-0.165	-0.026	-0.016	-0.265	-0.183
NomRapP	0.476	0.324	1	-0.394	-0.297	-0.370	-0.661	-0.360
Total de Pontos	-0.241	-0.165	-0.394	1	0.282	0.240	0.582	0.402
Total de Fixações	-0.251	-0.026	-0.297	0.282	1	0.809	0.598	0.306
% de Regressões	-0.371	-0.016	-0.370	0.240	0.809	1	0.613	0.346
Tempo Total	-0.482	-0.265	-0.661	0.582	0.598	0.613	1	0.442
Total E+O	-0.268	-0.183	-0.360	0.402	0.306	0.346	0.442	1

Figure 32: Correlation Matrix obtained in scenario **S10**.

As the value of the correlations of these last two scenarios are not strong and it is not clear if they are significant, then, as mentioned in the previous section, SPSS was used to analyse the correlation matrices for each scenario. Survey and selection of the type of errors for the detection algorithm.

For scenario **S12**, the Shapiro-Wilk test is used, because n is less than 50 ($n = 15$). Through this test, it can be seen that the attribute "Cancelamento", the "Total de Tempo" and the "Total E+O" do not follow a normal distribution (P) because of $P < 0.05$. Therefore, correlations will be calculated using Spearman's ρ. As for scenario S9, in this scenario, two negative correlations with values below -0.55 and a positive one above 0.55 were obtained for the memory test result. Only these 3 correlations are significant. Regarding the test that measures attention deficit, there are 3 negative correlations, which were significant, with the attributes “Total de Fixações”, “% de Regressões” and “Total E+O”, as shown in Figure 33.

			Wisc	Cancelamento	NomRapP	Total de Pontos	Total de Fixações	% de Regressões	Tempo Total	Total E+O
Spearman's rho	Wisc	Correlation Coefficient	1.000	0.335	.571*	-0.111	-.563*	-.600*	-0.239	-0.133
		Sig. (2-tailed)		0.222	0.026	0.695	0.029	0.018	0.391	0.636
		N	15	15	15	15	15	15	15	15
	Cancelamento	Correlation Coefficient	0.335	1.000	0.161	-0.233	-.569*	-.564*	-0.482	-.758**
		Sig. (2-tailed)	0.222		0.566	0.404	0.027	0.029	0.069	0.001
		N	15	15	15	15	15	15	15	15
	NomRapP	Correlation Coefficient	.571*	0.161	1.000	-0.454	-.675**	-.633*	-.629*	0.016
		Sig. (2-tailed)	0.026	0.566		0.089	0.006	0.011	0.012	0.956
		N	15	15	15	15	15	15	15	15
	Total de Pontos	Correlation Coefficient	-0.111	-0.233	-0.454	1.000	0.243	0.182	.639*	0.294
		Sig. (2-tailed)	0.695	0.404	0.089		0.383	0.516	0.010	0.287
		N	15	15	15	15	15	15	15	15
	Total de Fixações	Correlation Coefficient	-.563*	-.569*	-.675**	0.243	1.000	.900**	.646**	0.442
		Sig. (2-tailed)	0.029	0.027	0.006	0.383		0.000	0.009	0.099
		N	15	15	15	15	15	15	15	15
	% de Regressões	Correlation Coefficient	-.600*	-.564*	-.633*	0.182	.900**	1.000	.532*	0.306
		Sig. (2-tailed)	0.018	0.029	0.011	0.516	0.000		0.041	0.268
		N	15	15	15	15	15	15	15	15
	Tempo Total	Correlation Coefficient	-0.239	-0.482	-.629*	.639*	.646**	.532*	1.000	0.454
		Sig. (2-tailed)	0.391	0.069	0.012	0.010	0.009	0.041		0.089
		N	15	15	15	15	15	15	15	15
	Total E+O	Correlation Coefficient	-0.133	-.758**	0.016	0.294	0.442	0.306	0.454	1.000
		Sig. (2-tailed)	0.636	0.001	0.956	0.287	0.099	0.268	0.089	
		N	15	15	15	15	15	15	15	15

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 33: Correlation Matrix obtained in scenario **S12**.

For scenario **S13**, the Kolmogorov-Smirnov test is used, because n is greater than 50 (n = 107). The population under analysis only follows a normal distribution (P>0.05), for the attributes “Cancelamento” and “% de Regressões”. Therefore, as for the previous scenario, Spearman’s ρ will have to be used to calculate the correlations. For this scenario, significant correlations were obtained between the result of the memory test and the other attributes, although the values were not very high. Regarding the result of the attention test, there are two significant correlations, which is the positive correlation with the result of the memory test and the positive correlation between the result of the rapid naming test.

In scenario **S14**, the population under analysis only follows a normal distribution (P>0.05), for the attribute “% de Regressões”. As in the other scenarios, Spearman’s ρ was used to calculate the correlations. For the attribute related to the result of the memory test, values were obtained identical to those of scenario **S13**. Regarding the attribute related to the result of the attention test, there were two significant correlations, a negative one, which is the correlation with the attribute "Total E+O" and a positive correlation with the attribute related to the result of the rapid naming test, as shown in Figure 34.

			Wisc	Cancelamento	NomRapP	Total de Pontos	Total de Fixações	% de Regressões	Tempo Total	Total E+O
Spearman's rho	Wisc	Correlation Coefficient	1.000	.257**	.463**	-.212*	-.322**	-.343**	-.397**	-.235**
		Sig. (2-tailed)		0.004	0.000	0.019	0.000	0.000	0.000	0.009
		N	122	122	122	122	122	122	122	122
	Cancelamento	Correlation Coefficient	.257**	1.000	.282**	-0.126	-0.052	-0.044	-0.160	-.237**
		Sig. (2-tailed)	0.004		0.002	0.167	0.572	0.632	0.078	0.009
		N	122	122	122	122	122	122	122	122
	NomRapP	Correlation Coefficient	.463**	.282**	1.000	-.410**	-.433**	-.412**	-.625**	-.303**
		Sig. (2-tailed)	0.000	0.002		0.000	0.000	0.000	0.000	0.001
		N	122	122	122	122	122	122	122	122
	Total de Pontos	Correlation Coefficient	-.212*	-0.126	-.410**	1.000	.246**	.187*	.719**	.307**
		Sig. (2-tailed)	0.019	0.167	0.000		0.006	0.039	0.000	0.001
		N	122	122	122	122	122	122	122	122
	Total de Fixações	Correlation Coefficient	-.322**	-0.052	-.433**	.246**	1.000	.901**	.555**	.338**
		Sig. (2-tailed)	0.000	0.572	0.000	0.006		0.000	0.000	0.000
		N	122	122	122	122	122	122	122	122
	% de Regressões	Correlation Coefficient	-.343**	-0.044	-.412**	.187*	.901**	1.000	.524**	.321**
		Sig. (2-tailed)	0.000	0.632	0.000	0.039	0.000		0.000	0.000
		N	122	122	122	122	122	122	122	122
	Tempo Total	Correlation Coefficient	-.397**	-0.160	-.625**	.719**	.555**	.524**	1.000	.427**
		Sig. (2-tailed)	0.000	0.078	0.000	0.000	0.000	0.000		0.000
		N	122	122	122	122	122	122	122	122
	Total E+O	Correlation Coefficient	-.235**	-.237**	-.303**	.307**	.338**	.321**	.427**	1.000
		Sig. (2-tailed)	0.009	0.009	0.001	0.001	0.000	0.000	0.000	
		N	122	122	122	122	122	122	122	122

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 34: Correlation Matrix obtained in scenario **S14**.

With these results, it can be concluded that the memory deficit can influence more the activities results, while the attention deficit tends not to influence. It can also be said that, in general, the greater the memory capacity the number of fixations and regressions is smaller.

8

CORRELATING MEMORY AND ATTENTION WITH PERFORMANCE - GENERALISATION

In this chapter, the study will be carried out, identical to those described in the previous chapter, with data coming from a new data collection. This collection was carried out between October and November in a group of schools in *Barcelos*. The collection was carried out in children aged 5 to 14, but due to lack of time, this chapter will only use data from children aged 5 to 11.

The population study used in the previous chapter will also be carried out.

8.1 STUDY DESCRIPTION

In this study, the population are children from 5 to 11 years old, having a total of 202 children. These children belong to the *Agrupamento Vertical de Escolas de Vila Cova* of Barcelos. Of these children, 23 are 5 years old, 36 are 6 years old, at 7 years old there are 25 children, at 8 years old there are 34, 20 are 9 years old and there are 44 children between 10 and 11. Table 7 shows the age division by school and year in more detail.

The population study used in the previous chapter will also be carried out. Getting in total 354 children.

8.1.1 *Exercises used, images*

As in the previous study (Chapter 7), two diagnostic tests were used, one for memory capacity and one for attention capacity. The rapid naming test was also used. These tests are represented by Figures 45, 46, 48, 49 (in Appendix A).

8.1.2 *Sample*

Of the 202 respondents, it was only possible to use the data from 181 because of problems with the data collected during the rapid naming test or cases where there is no result for

Table 7: Total of children by age and school year

Age	Year and School	Total	Age	Year and School	Total
5	Jardim de Infância Creixomil	3	8	2ºano - Perelhal	1
5	Jardim de Infância de Vila Cova	11	8	2ºano - Vila Cova	1
5	Jardim de Infância Perelhal	8	8	3ºano - Creixomil	3
5	1ºano - Vila Cova	1	8	3ºano - Perelhal	5
6	1ºano - Creixomil	6	8	3ºano - Vila Cova	18
6	1ºano - Perelhal	4	8	4ºano - Vila Cova	5
6	1ºano - Vila Cova	25	9	3ºano - Perelhal	1
6	2ºano - Vila Cova	1	9	4ºano - Creixomil	2
7	2ºano - Creixomil	5	9	4ºano - Perelhal	13
7	2ºano - Perelhal	5	9	4ºano - Vila Cova	21
7	2ºano - Vila Cova	9	9	5ºano - Vila Cova	3
7	3ºano - Creixomil	1	10	4ºano - Vila Cova	4
7	3ºano - Perelhal	3	10	5ºano - Vila Cova	36
7	3ºano - Vila Cova	2	11	5ºano - Vila Cova	4
8	2ºano - Creixomil	1			

the proof of attention capacity. Of these 177, 51 took the quick naming of colours test, and 126 took the quick naming of shapes and colours test. The memory test was not applied in children aged 5 years. So, the value of n for the quick naming of colours test is inferior, like is described in section 8.3.

Of the 354 values of the data with the whole population, it was possible to use 316 values. As in other cases, different filters will be applied later, and it is possible that fewer values will be used.

8.2 COLLECTED DATA

For this study, Script1 described in section 7.2 is used. With this script, the files "Info _ExecsTotal.json" and "Emotions_Execs.json" were created, which contained the information also described in the same section, bur only with the executions of this collection. Through the "Info_ExecsTotal.json" file, it will obtain the information of all executions related to the tests used in this study.

Through the files mentioned above, and from the same process used in the previous study, a new file was obtained with the data described in Dataset2, in subsection 7.2.1.

8.3 DESCRIPTION

This study was used to show that with a new sample, the result obtained in the previous chapter is maintained or shown to be stronger or not. Therefore, in this case, the results are only analysed using the SPSS program. As noted above, this study will use 2 population sets, one with data from the new collection and the other with data from all collections. Therefore, 6 scenarios will be used, 3 (**S15**, **S16**, **S17**) referring to the population of data collection between October and November, and another 3 scenarios (**S18**, **S19**, **S20**) with data collected from the entire population. The 6 scenarios are described below:

- **S15 and S18** - Only the data from the quick naming of colour.
- **S16 and S19** - Only the data from the quick naming of shapes and colours.
- **S17 and S20** - Both tests.

Like in the previous study, in scenario **S15** it was necessary to make a filter to select only children who took both tests, so the attributes "Wisc" and "Cancelamento" must be greater than or equal to zero. This includes only the children who are older than 5 years because the wisc test is only applied to children with 6 or more years. To this, a filter has been added to select the experiment corresponding to the rapid colour naming test. With these filters, the dataset got an n=34. In scenario **S16**, it was used the filter for the tests and the filter to select the experiment id corresponding to the quick naming test of shape and colours. For this scenario, the value of n is 126. In scenario **S17**, the only filter that was used is the filter for select in the attributes "Wisc" and "Cancelamento" the values greater than or equal to zero. This process it was repeated for the other 3 scenarios (**S18**, **S19**, **S20**).

For each scenario, it is necessary to check the normal distribution of each attribute that will be used to know which type of correlation to apply.

In scenario **S15**,for test the normality, it is necessary to do the Shapiro-Wilk, because the n value is less than 50. In scenario **S16**, the Kolmogorov-Smirnov test was applied because the value of n is greater than 50. In scenario **S17**, it was also applied the Kolmogorov-Smirnov. For scenario **S18**, the Shapiro-Wilk was applied, because the n value is 44. In scenarios **S19** and **S20**, it is necessary to do the Kolmogorov-Smirnov test because the n value is 234 and 278, respectively.

8.4 RESULTS

For scenario **S15**, the Shapiro-Wilk test is used. Through this test, it can be seen that the population under analysis doesn't follow a normal distribution ($P<0.05$) in the attribute "Total de Pontos", the "Total de Fixações", the "Total de Tempo", and the "Total E+O". That's why, correlations will be calculated using Spearman's ρ. In the attributes "Wisc" and "Cancelamento" there is no statistically significant correlation. In relation to the attribute "NomRap", the others attributes have a negative correlation, which is significant, as shown in Figure 35.

Correlations

			Wisc	Cancelamento	NomRapP	Total de Pontos	Total de Fixações	% de Regressões	Tempo Total	Total E+O
Spearman's rho	Wisc	Correlation Coefficient	1.000	0.310	0.297	-0.031	-0.129	-0.220	-0.264	-0.122
		Sig. (2-tailed)		0.090	0.104	0.868	0.489	0.235	0.152	0.513
		N	31	31	31	31	31	31	31	31
	Cancelamento	Correlation Coefficient	0.310	1.000	0.077	-0.129	-0.194	-0.245	-0.069	-0.086
		Sig. (2-tailed)	0.090		0.679	0.490	0.296	0.184	0.711	0.644
		N	31	31	31	31	31	31	31	31
	NomRapP	Correlation Coefficient	0.297	0.077	1.000	-.758**	-.757**	-.547**	-.985**	-.604**
		Sig. (2-tailed)	0.104	0.679		0.000	0.000	0.001	0.000	0.000
		N	31	31	31	31	31	31	31	31
	Total de Pontos	Correlation Coefficient	-0.031	-0.129	-.758**	1.000	.662**	0.243	.788**	.408*
		Sig. (2-tailed)	0.868	0.490	0.000		0.000	0.188	0.000	0.023
		N	31	31	31	31	31	31	31	31
	Total de Fixações	Correlation Coefficient	-0.129	-0.194	-.757**	.662**	1.000	.580**	.744**	.411*
		Sig. (2-tailed)	0.489	0.296	0.000	0.000		0.001	0.000	0.022
		N	31	31	31	31	31	31	31	31
	% de Regressões	Correlation Coefficient	-0.220	-0.245	-.547**	0.243	.580**	1.000	.510**	0.348
		Sig. (2-tailed)	0.235	0.184	0.001	0.188	0.001		0.003	0.055
		N	31	31	31	31	31	31	31	31
	Tempo Total	Correlation Coefficient	-0.264	-0.069	-.985**	.788**	.744**	.510**	1.000	.527**
		Sig. (2-tailed)	0.152	0.711	0.000	0.000	0.000	0.003		0.002
		N	31	31	31	31	31	31	31	31
	Total E+O	Correlation Coefficient	-0.122	-0.086	-.604**	.408*	.411*	0.348	.527**	1.000
		Sig. (2-tailed)	0.513	0.644	0.000	0.023	0.022	0.055	0.002	
		N	31	31	31	31	31	31	31	31

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 35: Correlation Matrix obtained in scenario **S15**.

In scenario **S16**, none of the attributes follow the normal distribution. Therefore, Spearman's ρ will have to be used to calculate the correlations. For this scenario, all attributes except the attribute "Total de E+O" have significant correlations (despite having low values) with the attribute that represents the result of the memory test. The attribute that defines the result of the attention test has four significant correlations. Two of them are positive correlations with attributes "Wisc" and "NomRap", and the others are negative and are related to attributes "% de Regressões" and "Total de Tempo". The attribute related to the result of the rapid naming test has significant correlations with all attributes. Figure 36 shows the results of the correlation matrix.

Correlations

			Wisc	Cancelamento	NomRapP	Total de Pontos	Total de Fixações	% de Regressões	Tempo Total	Total E+O
Spearman's rho	Wisc	Correlation Coefficient	1.000	.254**	.227*	-.213*	-.212*	-.228*	-.271**	-0.054
		Sig. (2-tailed)		0.004	0.011	0.017	0.017	0.010	0.002	0.545
		N	126	126	126	126	126	126	126	126
	Cancelamento	Correlation Coefficient	.254**	1.000	.286**	-0.165	-0.151	-.179*	-.213*	-0.110
		Sig. (2-tailed)	0.004		0.001	0.064	0.091	0.045	0.017	0.220
		N	126	126	126	126	126	126	126	126
	NomRapP	Correlation Coefficient	.227*	.286**	1.000	-.710**	-.618**	-.485**	-.816**	-.414**
		Sig. (2-tailed)	0.011	0.001		0.000	0.000	0.000	0.000	0.000
		N	126	126	126	126	126	126	126	126
	Total de Pontos	Correlation Coefficient	-.213*	-0.165	-.710**	1.000	.803**	.479**	.843**	.346**
		Sig. (2-tailed)	0.017	0.064	0.000		0.000	0.000	0.000	0.000
		N	126	126	126	126	126	126	126	126
	Total de Fixações	Correlation Coefficient	-.212*	-0.151	-.618**	.803**	1.000	.698**	.782**	.329**
		Sig. (2-tailed)	0.017	0.091	0.000	0.000		0.000	0.000	0.000
		N	126	126	126	126	126	126	126	126
	% de Regressões	Correlation Coefficient	-.228*	-.179*	-.485**	.479**	.698**	1.000	.673**	.472**
		Sig. (2-tailed)	0.010	0.045	0.000	0.000	0.000		0.000	0.000
		N	126	126	126	126	126	126	126	126
	Tempo Total	Correlation Coefficient	-.271**	-.213*	-.816**	.843**	.782**	.673**	1.000	.410**
		Sig. (2-tailed)	0.002	0.017	0.000	0.000	0.000	0.000		0.000
		N	126	126	126	126	126	126	126	126
	Total E+O	Correlation Coefficient	-0.054	-0.110	-.414**	.346**	.329**	.472**	.410**	1.000
		Sig. (2-tailed)	0.545	0.220	0.000	0.000	0.000	0.000	0.000	
		N	126	126	126	126	126	126	126	126

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 36: Correlation Matrix obtained in scenario **S16**.

As mentioned above, in scenario **S17**, the Kolmogorov-Smirnov test is used, because n is greater than 50 (n = 157). None of the attributes under analysis follows a normal distribution. For calculating correlations the Spearman's ρ, as in the other scenarios, was used. The "Wisc" attribute, in this scenario, has significant correlations with all attributes except the attribute "Total de Pontos" and "Total de E+O", two positive correlations with the attribute "Cancelamento" and "NomRap", and the others correlations are negative. About the attribute related to the result of the attention test, one less statistically significant correlation was obtained compared to scenario s16. This correlation that disappears is related to the "Total de Tempo" attribute. Like in the scenario **S16**, the attribute related to the result of the quick naming test has significant correlations with all attributes.

For scenario **S18**, as mentioned before, the Shapiro-Wilk test is used to test the normal distribution. In this scenario, only the attribute "% de Regressões" follows a normal distribution. The correlations will be calculated using Spearman's ρ. In this scenario, two negative correlations, and two positive correlations were obtained for the memory test result. The negative correlations are with the attributes "% de Regressões" and "Tempo Total", and the positives are with the attributes "Cancelamento" and, "NomRap". Regarding the test that measures attention deficit, there are 2 negative correlations, which were significant, with the attributes "% de Regressões" and "Total E+O", and there is one positive correlation significant with the attribute "Wisc". The attribute "NomRap" has statistically significant correlations with all attributes except the "Cancelamento" attribute.

In scenario **S19**, the Kolmogorov-Smirnov test is used, because n is greater than 50. Only one of the attributes follow the normal distribution. Therefore, Spearman's ρ will have to be used to calculate the correlations. For this scenario, all attributes have a significant correlation (despite having low values), with the attribute that represents the result of the memory test. The attribute that defines the result of the attention test, like in scenario **S18**, has two significant positive correlations positive. But, it only has one significant negative correlation with the attribute "Total de Tempo". The attribute related to the result of the quick naming test has significant correlations with all attributes, as in the scenario **S16** and **S17**.

In scenario **S20**, the Kolmogorov-Smirnov test is used. Like in the previous scenario, only the "% de Regressões" attribute follows a normal distribution. For calculating correlations, it was used Spearman's ρ, as in the other scenarios. The "Wisc" attribute, in this scenario, has significant correlations with all attributes except the attribute "Total de Pontos", two positive correlations with the attribute "Cancelamento" and "NomRap", and the others correlations are negative. About the "Cancelamento" attribute, it has 4 significant correlations. Two negative correlations with the attributes "Total de E+O" and "Tempo Total", and two positive correlations with the attributes "Cancelamento" and, "NomRap.

With these results, it can be concluded, that the memory deficit can influence the experience associated with the rapid naming of shapes and colours. And, in general, the memory deficit influences more than the attention deficit, which tends only to correlate with the number of errors and omissions or with the percentage of regressions.

9

CONCLUSION

In this chapter, a retrospective of the work developed and a discussion of the contribution of the results obtained in this thesis will be shown.

This work was started with the objective of finding knowledge of data that we did not know if we were going to collect, which instruments to use to collect them and what is the best method to analyse the set of these data.

Initially, it was studied what serious games are, where they are applied and what is the advantage of using them for health and therapy. As the *Centro Neurosensorial de Braga* already uses eye movement tracking in some tests, it was important to study the types of eye movements that exist, to later realise the results coming from the Eye Tracker sensor. There was also reading about emotions because they are also studied in the CNB. Although the CNB already implemented the emotions that are measured throughout the tests, due to the API in use, it was tried to understand what other emotions would exist and the difference that could be between them. During this time, there were several visits to the CNB to understand the data collection system, the flaws that might exist in the already implemented system. After this work had been done, the data was studied and worked with to understand the best way to combine them, as described in Study 1 in Chapter 4.

As in Study 1, the task did not involve a correction for a later phase, it was decided to use another test, the rapid naming test, where more details about the test result can be extracted. Before there was mass data collection, these tests were put into operation and some data was collected to understand how to combine the test results with the data collected from the sensors.

With studies 2 and 3 (Chapters 5 and 6), it is clear that the association rules were not the best technique to be used, because no rules were obtained or they were not relevant (as they did not have great support). Through the rules of the induction rules, although they aren't used for the classification of a next dataset, they were used to see the heartbeats according to the experience or according to the zone the patient was looking at. It was noted that the experiment to detect the face representing happy and the zones representing joy generated a higher average beats per minute. As for the rapid naming of shapes and colour test, it can be seen that the zones that represent rectangles and zones that represent the black, yellow and red colours tend to have higher BPM values. As for the quick naming of colours test, it can be seen that the zones that represent the green colour tend to present higher BPM values, despite the other values being very close. It should not be forgotten that in study 3 you do not hear outliers cleaning due to the software crashing during detection of them.

Study 4 (Chapter 7), was the study that had the most interesting results, due to the introduction of new variables that were not available when the previous studies were done (for example, the correction of memory and attention deficit detection tests). With these new data, it was possible to better characterise the respondent and try to relate their profile with the result of the rapid naming tests. With a simple graphic that represents the eye-tracking of the test, you can see the distinction between people with a high deficit of attention and memory compared to someone who does not have these deficits. With the results obtained from the correlations, it can be seen that children with good memory capacity tend to fix less and make fewer regressions, which coincides with what is visualised in the graphs that represent only the fixations throughout the test. Although some correlation results are not significant, this was the process that brought more interesting results to analyse and that became more useful for the CNB.

Chapter 8 shows us that despite using a different sample, in general, the results are identical to the study referred to in Chapter 7. Using all population, the idea that the memory capacity can influence the number of fixations and regressions and that the attention capacity has more influence on the number of errors and omissions is also reinforced.

With this work, it was also possible to see that the sensors used and that can bring more advantage is the eye tracker, maybe, because it was the sensor that is more continuous. What proved less useful was the oximeter. Because it only gave heartbeat information every 2 seconds, which becomes a large interval, when the other information is collected at intervals less than 1 second and, in the activities of recognition the emotions, often these does not last more than 4 seconds.

With the work developed throughout this year, it was possible to show that through the data collected, during the tests and the data coming from the sensors, and using data analysis it is possible to create new knowledge.

To conclude, DM in healthcare is quite complex because it involves a large number of variables that come from different sensors, which often capture data at different time intervals, which makes it more complicated to combine this data. With the data collected, the correlation was what brought the most advantages, as mentioned above, but there are other techniques that, depending on the data available, can also generate relevant information.

9.1 CONTRIBUTIONS

This thesis project contributes as follows:

- **Changing the time interval for collecting images**.

  These changes are due to the fact that during the data collection for this project, some problems were raised, such as emotions being only calculated at intervals of 500 ms, not having an image taken initially to analyse the emotion at the beginning of the test. That's why the platform was updated and now calculates emotions at 250ms intervals and starts at instant zero.

- **Creating a new chart for the CNB platform**.

  The charts were created for Study 4, referred to in Chapter 7 in the 7.3 section. These are useful to have a more detailed visualisation of the eye movements throughout the execution and to understand if the movements are coarse or not.

- **Automatic correction platform for quick naming test**.

  During the data collection, for this project, it was noticed the difficulty that the rapid naming test can bring. In this test, whoever evaluates it has to monitor what the patient is saying, point out where he makes mistakes and also has to control the test time. Due to this problem, the idea of creating a platform that made the automatic correction, through collected audio, of tests of this type arose. This platform was developed within the scope of the discipline "Project" of the degree in Computer Science.

- **Master's Thesis Proposal**.

  Through the previous project, and the difficulties encountered in performing these tests automatically, it was decided to extend this project to a Master's Thesis, to explore this problem of automatic correction and generalise the correction to any type of test.

- **Article in *Revista Spot***

  During this journey, it was possible to observe interesting results. Therefore, Dr Ana Paula found it interesting to talk about them, and in September there was the opportunity to write an article in *Revista Spot* (a magazine with great diffusion and popularity in the Braga region). This was published in the October magazine.

- **Paper in *WorldCist'22***.

  At the same time as data collection, in October and November, another article was written on the results obtained in the study described in chapter 7. This was accepted at *WorldCist'22* (10th World Conference on Information Systems and Technologies) and, will be published in April (de Pinho et al., 2022).

9.2 FUTURE WORK

As written in Chapter 8, there was a new data collection from mid-October to the end of November. In this collection, the tests carried out previously, in the other collections, and other tests that could help characterise the child better were carried out. An electroencephalogram was performed during the rapid naming test and the recognition of emotions test. As there was a large amount of data collection (n=316, from 5 to 14 years old), and the electroencephalogram was being carried out, the collection per child took longer than expected. Because of this, it was impossible to analyse all the data from the last collection, but these will be studied and data analysis methods will be applied, to try, to discover new patterns and generate new knowledge in this area. With the results of the study of these data, it is thought to be able to write an article in a journal in the field of neuroscience.

As a perspective for future work, it would be interesting to explore the results coming from other sensors, such as balance meter, apply new DM methods to the datasets and collect data from a larger population in which to try to obtain more significant data.

It would also be interesting to explore the following ideas:

- **Use voice recording during the test** - use the audio to notice when the person makes a mistake or "chokes" and try to understand what happens to the eye movement and emotions at that time and try to extract patterns for the mistakes and even enable a correction evidence more effectively.
- **When emotions occur** - Understand if emotions occur as a result of running the test or if an emotion is intrinsic to the child.

BIBLIOGRAPHY

Richard A. Abrams, David E. Meyer, and Sylvan Kornblum. Speed and accuracy of saccadic eye movements: Characteristics of impulse variability in the oculomotor system. *Journal of Experimental Psychology: Human Perception and Performance*, 15(3):529–543, 1989. doi: 10.1037/0096-1523.15.3.529. URL https://doi.org/10.1037/0096-1523.15.3.529.

Tad T. Brunyé, Trafton Drew, Donald L. Weaver, and Joann G. Elmore. A review of eye tracking for understanding and improving diagnostic interpretation. *Cognitive Research: Principles and Implications*, 4(1), February 2019. doi: 10.1186/s41235-019-0159-2. URL https://doi.org/10.1186/s41235-019-0159-2.

Benjamin T. Carter and Steven G. Luke. Best practices in eye tracking research. *International Journal of Psychophysiology*, 155:49 – 62, 2020. ISSN 0167-8760. doi: https://doi.org/10.1016/j.ijpsycho.2020.05.010. URL http://www.sciencedirect.com/science/article/pii/S0167876020301458.

Geetika Chawla, Savita Bamal, and Rekha Khatana. Big data analytics for data visualization: Review of techniques. *International Journal of Computer Applications*, 182, 10 2018. doi: 10.5120/ijca2018917977.

Daniel Cheng and Roel Vertegaal. An eye for an eye: A performance evaluation comparison of the <i>lc technologies and tobii</i> eye trackers. In *Proceedings of the 2004 Symposium on Eye Tracking Research amp; Applications*, ETRA '04, page 61, New York, NY, USA, 2004. Association for Computing Machinery. ISBN 1581138253. doi: 10.1145/968363.968378. URL https://doi.org/10.1145/968363.968378.

Rafaela de Pinho, Maria João Varanda Pereira, Ana Paula Azevedo, and Pedro Rangel Henriques. Relating Biometric Sensors with Serious Games Results. In Álvaro Rocha and et al., editors, *New Knowledge in Information Systems and Technologies, WorldCist'2022*, Advances in Intelligent Systems and Computing. Springer International Publishing, Cham, 1 edition, April 2022. (to be publised).

Bruno Samways dos Santos, Maria Teresinha Arns Steiner, Amanda Trojan Fenerich, and Rafael Henrique Palma Lima. Data mining and machine learning techniques applied to public health problems: A bibliometric analysis from 2009 to 2018. *Computers Industrial Engineering*, 138:106120, 2019. ISSN 0360-8352. doi: https://doi.org/10.

1016/j.cie.2019.106120. URL http://www.sciencedirect.com/science/article/pii/S0360835219305893.

Paul Ekman. An argument for basic emotions. *Cognition and Emotion*, 6(3-4):169–200, 1992. doi: 10.1080/02699939208411068. URL https://doi.org/10.1080/02699939208411068.

Gonzalo Esteban, Camino Fernández, Vicente Matellán, and José Gonzalo-Orden. Computer surgery 3d simulations for a new teaching-learning model. *2011 IEEE 1st International Conference on Serious Games and Applications for Health, SeGAH 2011*, 11 2011. doi: 10.1109/SeGAH.2011.6165445.

Ombretta Gaggi, Claudio Enrico Palazzi, Matteo Ciman, Giorgia Galiazzo, Sandro Franceschini, Milena Ruffino, Simone Gori, and Andrea Facoetti. Serious games for early identification of developmental dyslexia. *Comput. Entertain.*, 15(2), April 2017. doi: 10.1145/2629558. URL https://doi.org/10.1145/2629558.

Michael S. Gazzaniga, Todd F. Heatherton, and Veronese Maria Adriana Verissimo. *Ciencia psicologica: mente, cerebro e comportamento*. Artmed, 2005.

Evgeniy Yur'evich Gorodov and Vasiliy Vasil'evich Gubarev. Analytical review of data visualization methods in application to big data. *Journal of Electrical and Computer Engineering*, 2013:969458, Nov 2013. ISSN 2090-0147. doi: 10.1155/2013/969458. URL https://doi.org/10.1155/2013/969458.

A. Gosain and A. Kumar. Analysis of health care data using different data mining techniques. In *2009 International Conference on Intelligent Agent Multi-Agent Systems*, pages 1–6, 2009.

Simeng Gu, Fushun Wang, Nitesh P. Patel, James A. Bourgeois, and Jason H. Huang. A model for basic emotions using observations of behavior in drosophila. *Frontiers in Psychology*, 10:781, 2019. ISSN 1664-1078. doi: 10.3389/fpsyg.2019.00781. URL https://www.frontiersin.org/article/10.3389/fpsyg.2019.00781.

Makrufa Hajirahimova and Marziya Ismayilova. Big data visualization: Existing approaches and problems. *Problems of Information Technoligy*, 09:72–83, 01 2018. doi: 10.25045/jpit.v09.i1.07.

Markus Hofmann and Ralf Klinkenberg. *RapidMiner: Data mining use cases and business analytics applications*. CRC Press, 2016.

M. Ilayaraja and T. Meyyappan. Mining medical data to identify frequent diseases using apriori algorithm. In *2013 International Conference on Pattern Recognition, Informatics and Mobile Engineering*, pages 194–199, 2013.

Rachael.E. Jack, Oliver.G.B. Garrod, and Philippe.G. Schyns. Dynamic facial expressions of emotion transmit an evolving hierarchy of signals over time. *Current Biology*, 24(2): 187–192, 2014. ISSN 0960-9822. doi: https://doi.org/10.1016/j.cub.2013.11.064. URL https://www.sciencedirect.com/science/article/pii/S0960982213015194.

Sang Jun Lee and Keng Siau. A review of data mining techniques. *Industrial Management amp; Data Systems*, 101(1):41–46, 2001. doi: 10.1108/02635570110365989.

Peter J. Lang. The emotion probe: Studies of motivation and attention. *American Psychologist*, 50(5):372–385, 1995. doi: 10.1037/0003-066x.50.5.372.

Sally I. McClean. Data mining and knowledge discovery. In Robert A. Meyers, editor, *Encyclopedia of Physical Science and Technology (Third Edition)*, pages 229 – 246. Academic Press, New York, third edition edition, 2003. ISBN 978-0-12-227410-7. doi: https://doi.org/10.1016/B0-12-227410-5/00845-0. URL http://www.sciencedirect.com/science/article/pii/B0122274105008450.

Fabiano Koich Miguel. Psicologia das emoções: uma proposta integrativa para compreender a expressão emocional. *Psico-USF*, 20(1):153–162, 2015. doi: 10.1590/1413-82712015200114.

Arun K Pujari. *Data mining techniques*. Universities press, 2001.

Marco Rathschlag and Daniel Memmert. The influence of self-generated emotions on physical performance: An investigation of happiness, anger, anxiety, and sadness. *Journal of sport exercise psychology*, 35:197–210, 04 2013. doi: 10.1123/jsep.35.2.197.

Keith Rayner. Eye movement latencies for parafoveally presented words. *Bulletin of the Psychonomic Society*, 11(1):13–16, January 1978. doi: 10.3758/bf03336753. URL https://doi.org/10.3758/bf03336753.

Keith Rayner. The 35th sir frederick bartlett lecture: Eye movements and attention in reading, scene perception, and visual search. *Quarterly Journal of Experimental Psychology*, 62(8): 1457–1506, August 2009. doi: 10.1080/17470210902816461. URL https://doi.org/10.1080/17470210902816461.

Keith Rayner and Alexander Pollatsek. Eye movements and scene perception. *Canadian Journal of Psychology/Revue canadienne de psychologie*, 46(3):342–376, 1992. doi: 10.1037/h0084328. URL https://doi.org/10.1037/h0084328.

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*, pages 1–6, 2010.

Paula Alexandra Rego, Rui Rocha, Brígida Mónica Faria, Luís Paulo Reis, and Pedro Miguel Moreira. A serious games platform for cognitive rehabilitation with preliminary evaluation. *Journal of Medical Systems*, 41(1):10, Nov 2016. ISSN 1573-689X. doi: 10.1007/s10916-016-0656-5. URL https://doi.org/10.1007/s10916-016-0656-5.

James A Russell. A circumplex model of affect. *Journal of personality and social psychology*, 39 (6):1161, 1980.

Andreja Samčović. Serious games in military applications. *Vojnotehnicki glasnik*, 66:597–613, 07 2018. doi: 10.5937/vojtehg66-16367.

Günther Schuh, Gunther Reinhart, Jan-Philipp Prote, Frederick Sauermann, Julia Horsthofer, Florian Oppolzer, and Dino Knoll. Data mining definitions and applications for the management of production complexity. *Procedia CIRP*, 81:874 – 879, 2019. ISSN 2212-8271. doi: https://doi.org/10.1016/j.procir.2019.03.217. URL http://www.sciencedirect.com/science/article/pii/S2212827119305220. 52nd CIRP Conference on Manufacturing Systems (CMS), Ljubljana, Slovenia, June 12-14, 2019.

Hari Singh. Human eye tracking and related issues: A review. *International Journal of Scientific and Research Publications*, 2:1–9, 09 2012.

Samuel Stuart, Aodhan Hickey, Rodrigo Vitorio, Karen Welman, Stacy Foo, David Keen, and Alan Godfrey. Eye-tracker algorithms to detect saccades during static and dynamic tasks: a structured review. *Physiological Measurement*, 40(2):02TR01, feb 2019. doi: 10.1088/1361-6579/ab02ab. URL https://doi.org/10.1088%2F1361-6579%2Fab02ab.

Tarja Susi, Mikael Johannesson, and Per Backlund. Serious games: An overview, 2007.

Jessica L. Tracy and Daniel Randles. Four models of basic emotions: A review of ekman and cordaro, izard, levenson, and panksepp and watt. *Emotion Review*, 3(4):397–405, 2011. doi: 10.1177/1754073911410747. URL https://doi.org/10.1177/1754073911410747.

Rüdiger Wirth and Jochen Hipp. Crisp-dm: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining*, volume 1. Springer-Verlag London, UK, 2000.

Darius Zayeni, Jean-Philippe Raynaud, and Alexis Revet. Therapeutic and preventive use of video games in child and adolescent psychiatry: A systematic review. *Frontiers in Psychiatry*, 11:36, 2020. ISSN 1664-0640. doi: 10.3389/fpsyt.2020.00036. URL https://www.frontiersin.org/article/10.3389/fpsyt.2020.00036.

A

ILLUSTRATION OF THE EXERCISES USED IN THE STUDIES

This appendix contains the images of each experiment. Figure 37 represents the exercise used for first data analysis (Chapter 4).

Figures 38 to 44 represent the images for the recognition of emotions, used in study of Chapter 5, and figures 45 and 46 represent the BANC test, used in studies of Chapter 6, 7, and 8.

A.1 IMAGES USED IN THE CHAPTER ??

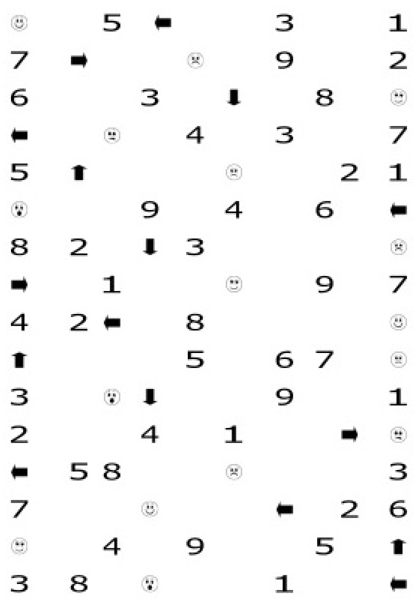


Figure 37: Experiment for study 1

A.2 IMAGES USED IN THE CHAPTER 5

Experiment 1

Represented in Figure 12

Experiment 2

Figure 38: Experiment to recognise happiness emotion

Experiment 3

Figure 39: Experiment to recognise sadness emotion

Experiment 4

Figure 40: Experiment to recognise fear emotion

Experiment 5

Figure 41: Experiment to recognise surprise emotion

Experiment 6

Figure 42: Experiment with repetition of images to recognise anger emotion

Experiment 7

Figure 43: Experiment with repetition of images to recognise fear emotion

Experiment 8

Figure 44: Experiment with repetition of images to recognise sadness emotion

A.3 Images used in both in Chapter 6, 7 and 8

Experiment 9

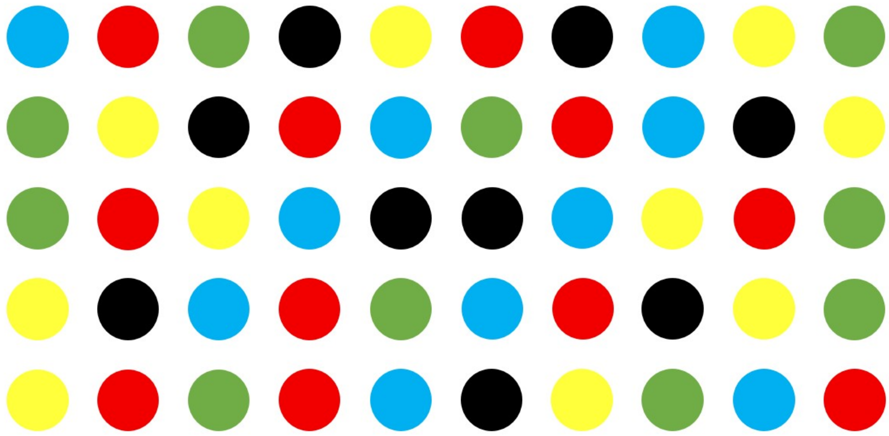


Figure 45: Quick naming of colours test

Experiment 10

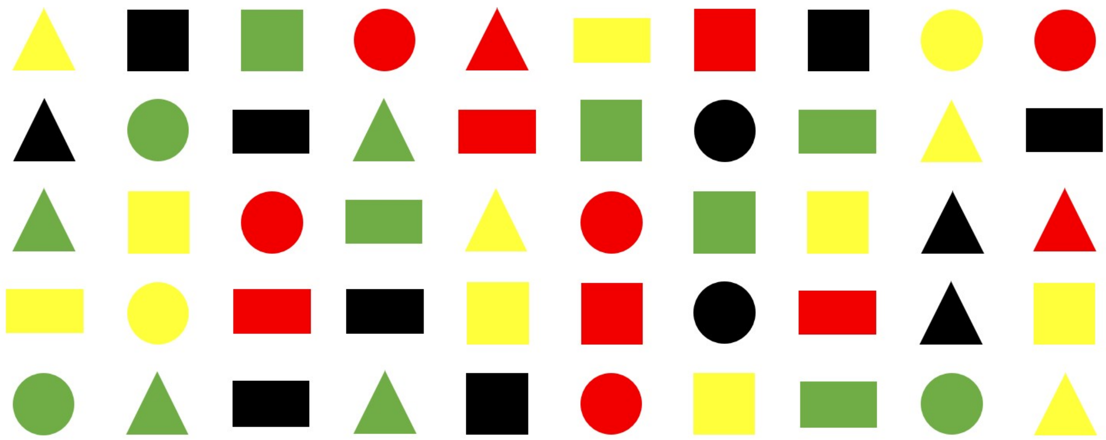


Figure 46: Quick naming of colours and shapes test

- **Tests used in the Chapter 7 and 8**

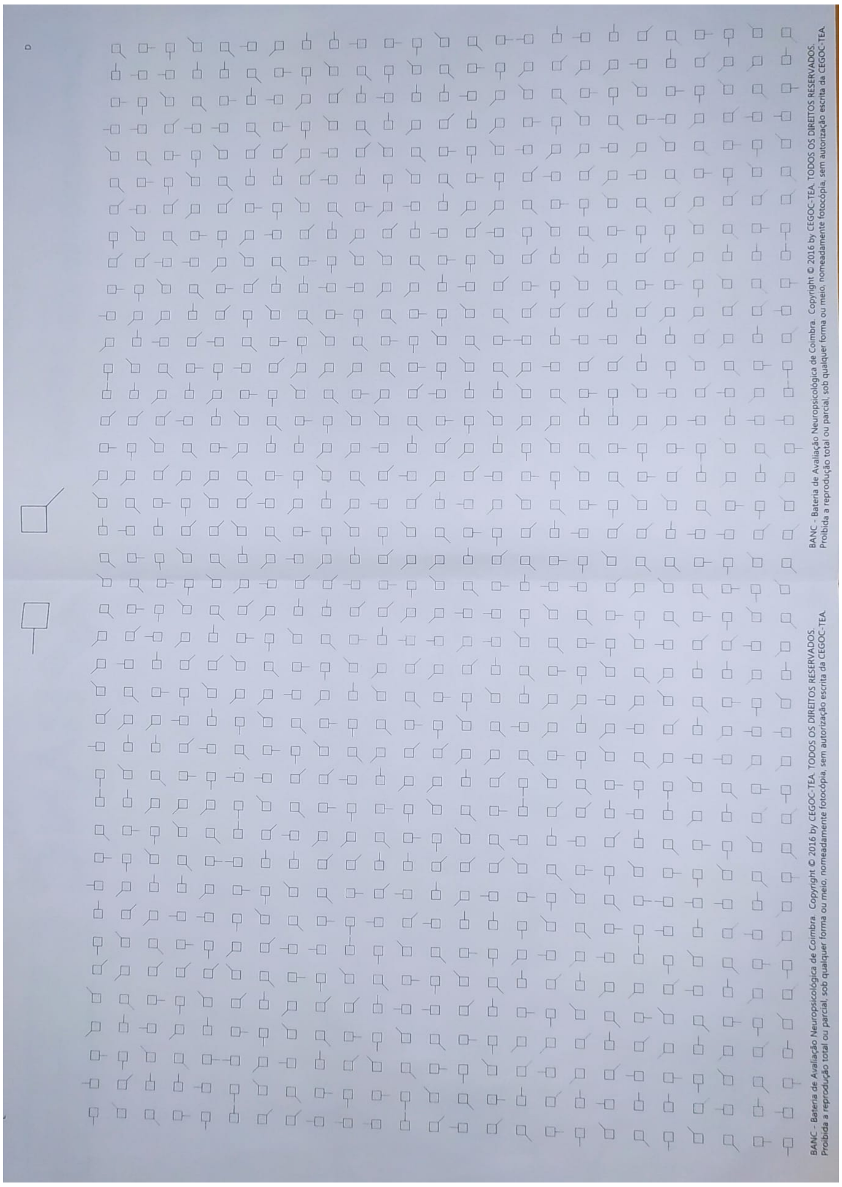


Figure 47: Diagnostic test of attention deficit

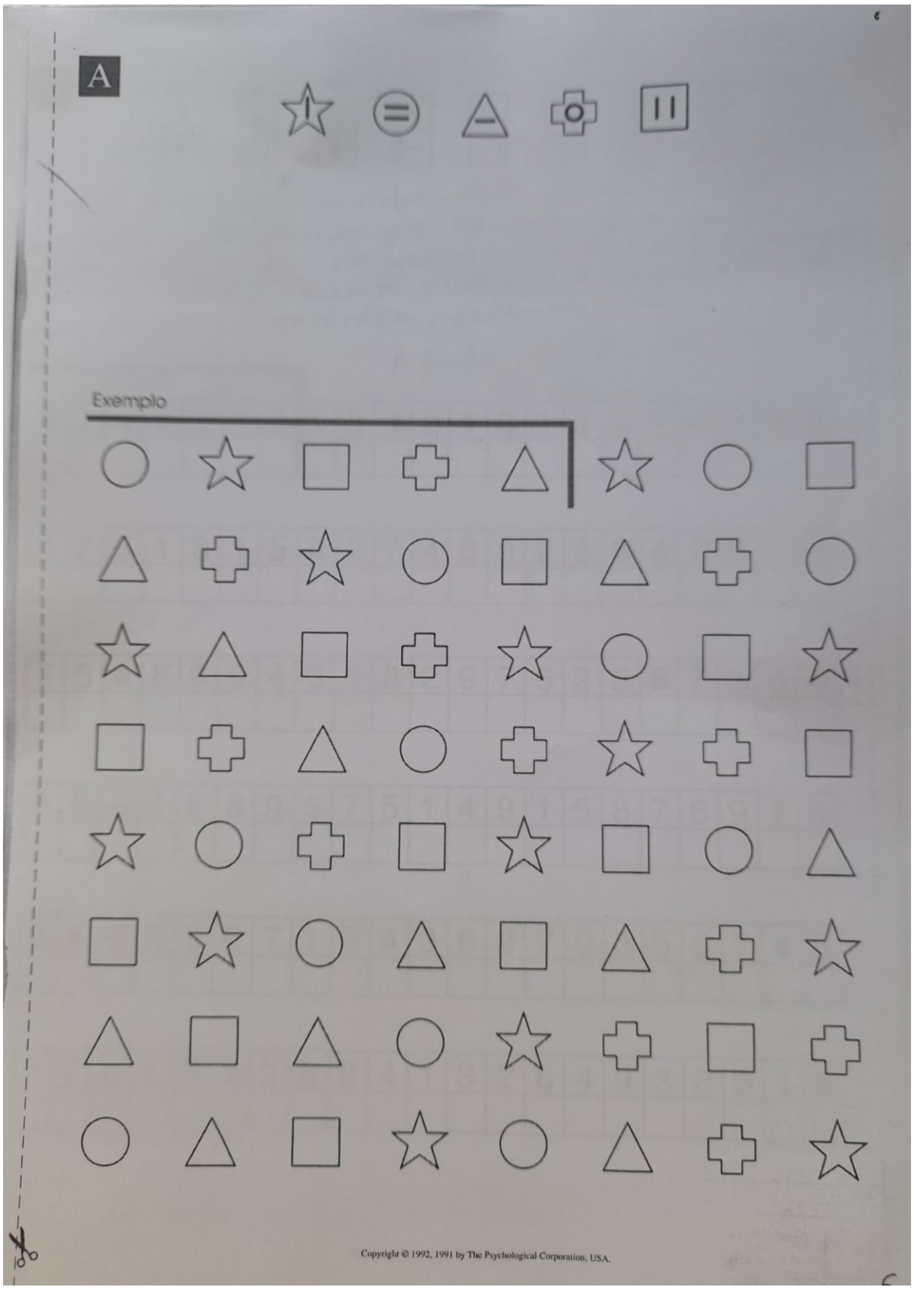


Figure 48: Diagnostic test of memory deficit, for children aged 6 to 7 years.

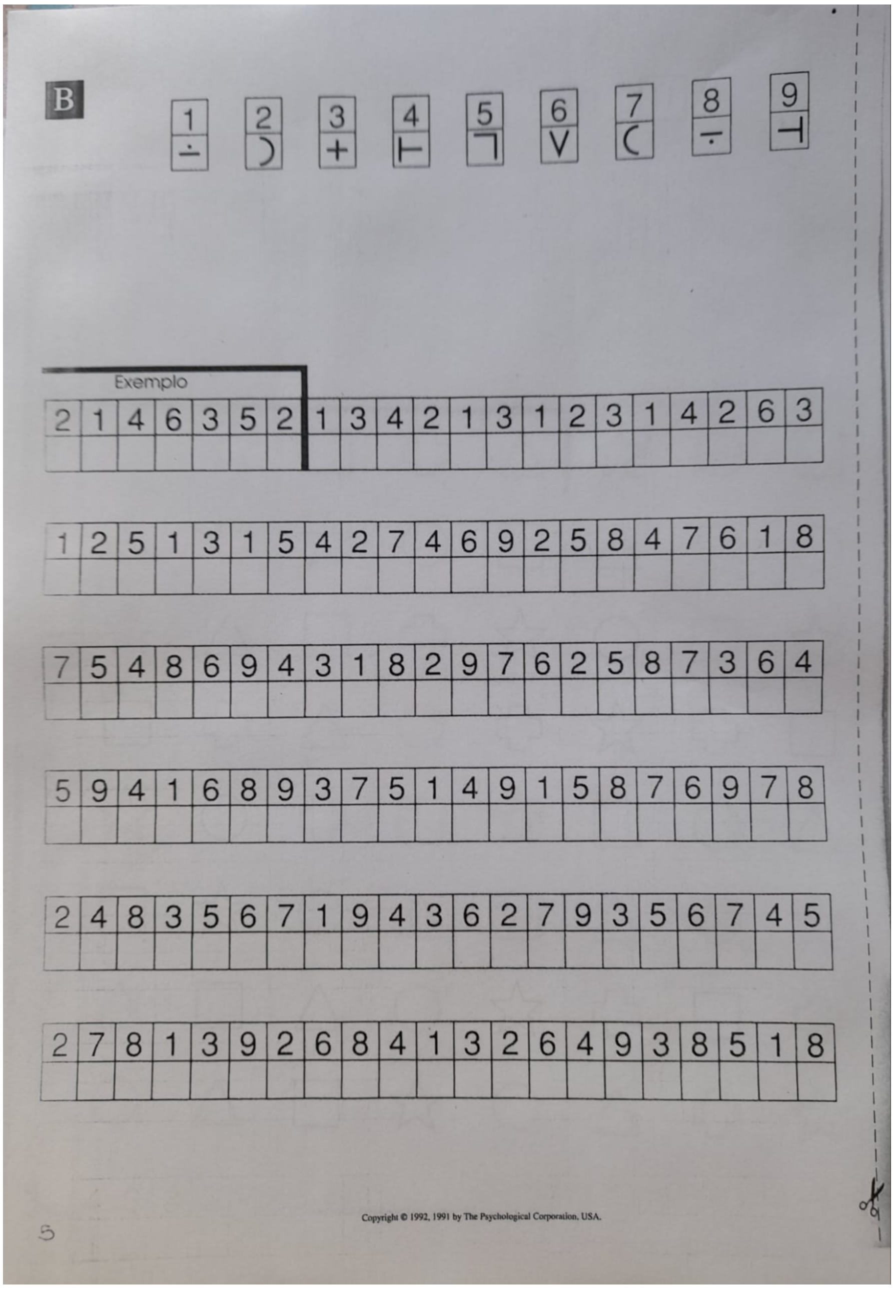


Figure 49: Diagnostic test of memory deficit, for children aged 8 to 16 years.