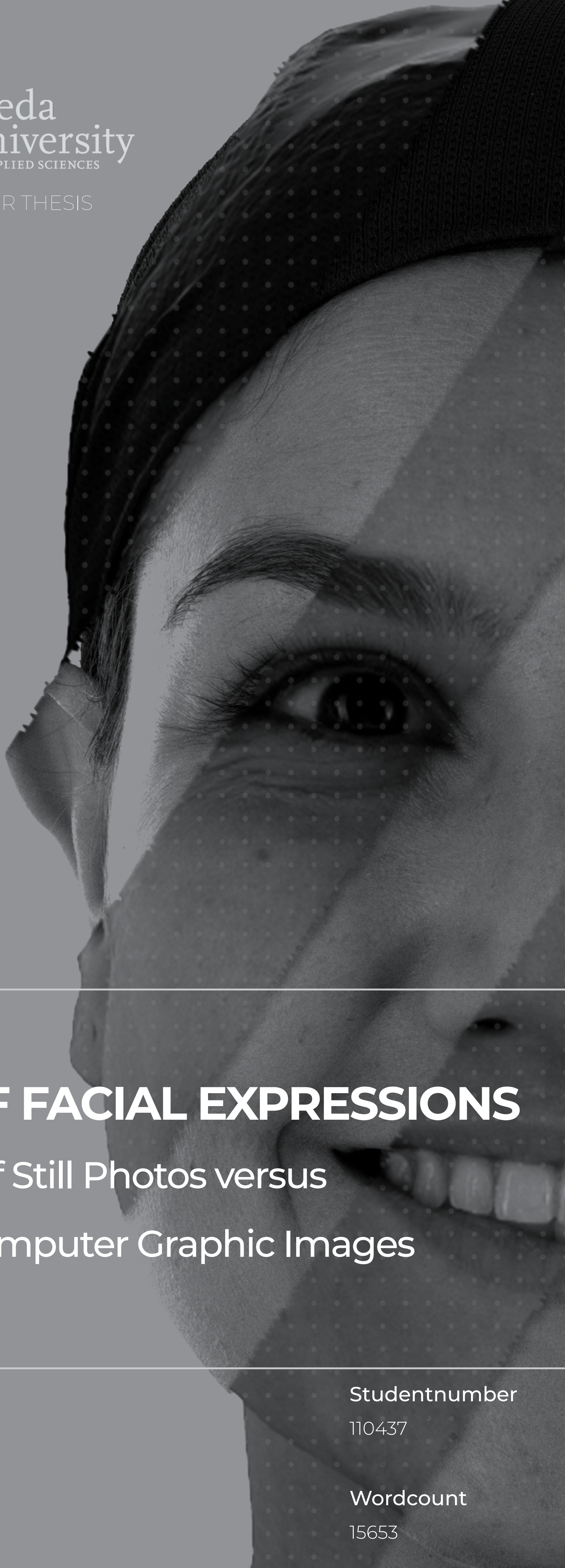

Breda University of Applied Sciences

MASTER THESIS

THE RECOGNITION OF FACIAL EXPRESSIONS

An Experiment of Still Photos versus Three Dimensional Computer Graphic Images

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DECLARATION OF AUTHORSHIP

I, Joey Relouw, declare that this thesis titled, The Recognition of Facial Expressions; An Experiment of Still Photos versus Three Dimensional Computer Graphic Images, and the work presented are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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ABSTRACT

Academy of Games and Media

Executive Master Media Innovation

The Recognition of Facial Expressions

An Experiment of Still Photos versus Three Dimensional Computer Graphic Images

By Joey Relouw

Modern techniques such as photogrammetry allow people, such as Visual Artists, Engineers, and Technical Developers, to capture real-life objects and convert them into three-dimensional digital objects. With the realism of computer graphics rapidly increasing over the last decade, new questions and challenges arise.

The ability to scan human faces through photogrammetry and applying them into realistic virtual environments raises the question whether three-dimensional scanning solutions can have the same effects as an image captured by a traditional photo camera. Modern techniques allow for high detailed 3D results, generating realistic facial expressions, however, such a comparison has not been researched yet. This study is based on the existing Multimodal Emotion Recognition Test method and presents the results of an between-subjects experiment. The study was executed in 2019, which explores the recognition of facial expressions, by comparing traditional photos and computer graphic scanned faces.

One hundred participants were tasked to recognize expressions of professional actors, who displayed a set of predetermined expressions. The displayed expressions consisted of; happiness, hot anger, sadness, disgust, elated joy, panic fear, irritation, contempt, despair, and anxiety. The results show that there are no noteworthy differences in the recognition of facial expressions between traditional photographs and computer graphic images. Even though the photographs scored slightly better in almost every subcategory, the difference is statistically insignificant. Interestingly, both groups do not show high percentages of expression recognition, most results had an average of only 50%. Hence the study recommends to not use unaltered photogrammetry data, and rather spend resources on the improvement of the realism of the computer graphics. Traditional photographs work best for fast, and less expensive results, while computer graphics allow for a more in-depth control where manipulability is beneficial, for example, in medical training simulators.

Keywords: photogrammetry, photographs, expressions, recognition, MERT, computer graphics

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Thank you all for your support,

Joey Relouw
Breda, November 2019

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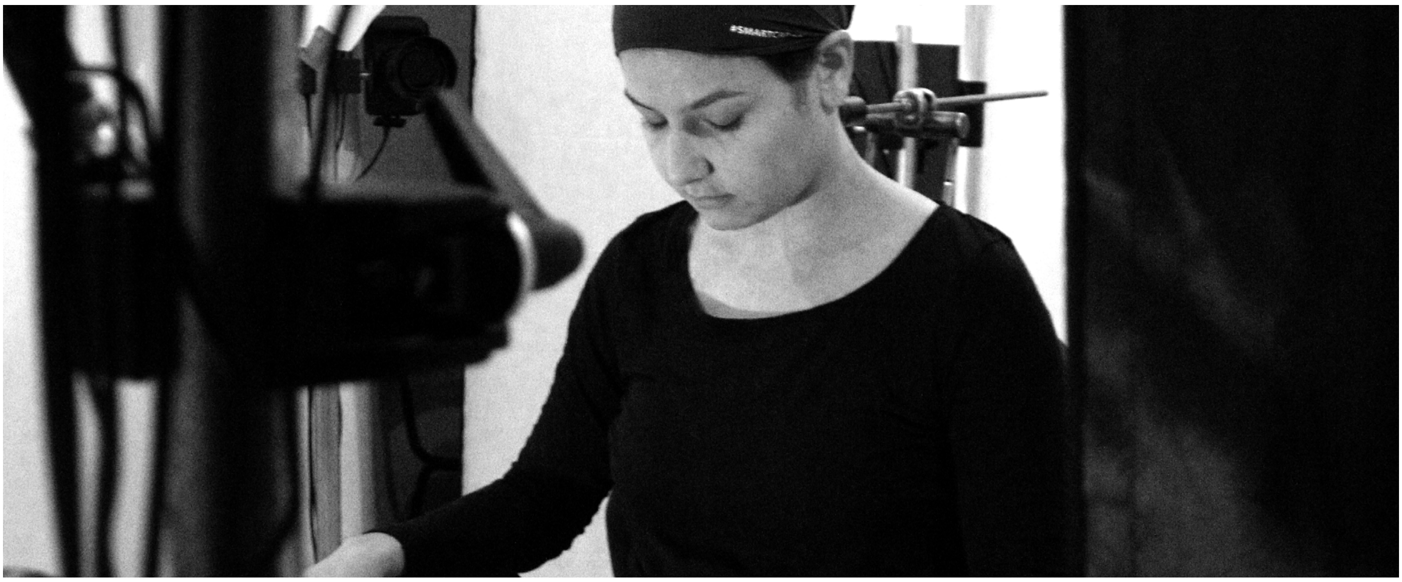

Figure 1: The actress preparing for the 3D face capturing.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
2D	**Two Dimensional:** A flat figure or shape that has two dimensions; length and width.
3D	**Three Dimensional:** An object with three dimensions; height, width, and depth.
AGM	**Academy of Games and Media:** One of the academies within BUas.
AI	**Artificial Intelligence:** Any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals.
API	**Application Programming Interface:** A communication protocol between a client and a server intended to simplify the building of client-side software.
-	**Base Mesh:** Template which drives blendshapes.
Big Six	**The basic expressions:** Most common and easy to recognize facial expressions.
-	**Blendshapes:** A method of 3D animation which deforms a target mesh trough deformed secondary meshes.
BUas	**Breda University of Applied Sciences:** Medium-sized government-funded higher education institute located in the Netherlands.
CG	**Computer Graphics:** Pictures and films created using computers with the help of specialized hardware and software.
DER	**Digital Enhanced Realities:** A research line of AGM.
FACS	**Facial Action Coding Systems:** A system to taxonomize human facial movements by their appearance on the face.
MERT	**Multimodal Emotion Recognition Test:** An instrument that measures the ability to recognize emotions.
-	**Polygon:** A type of geometry used to create 3D models.
R&D	**Research and Development:** Innovative activities undertaken by government and academic institutions designed to gather knowledge.
-	**Shader:** Act on 3D models and access the colors and textures used to draw the model.
SP	**Still Picture:** Abbreviation for indication during the testing phase.
-	**Stereoscopic viewing:** A computer technology that mimics the way humans naturally see to recreate depth.
-	**Topology:** The organization, flow, and structure of vertices/edges/faces of a 3D model.
UV	**Uncanny Valley:** A common unsettling feeling people experience when visual simulations closely resemble humans.
VE	**Virtual Environment:** A networked common operating space.
VIBE	**Virtual Humans in the Brabant Economy:** Project focusing on developing virtual humans to be used for training purposes.
VR	**Virtual Reality:** A simulated experience that can be similar to or completely different from the real world.

This thesis is proudly dedicated to my parents,
who always believed in my 'pupkes teikenen'.
My sister, who is my best friend.
And my girlfriend, for her love and encouragement.

Thank you for all the unconditional love, guidance and support you have given me.

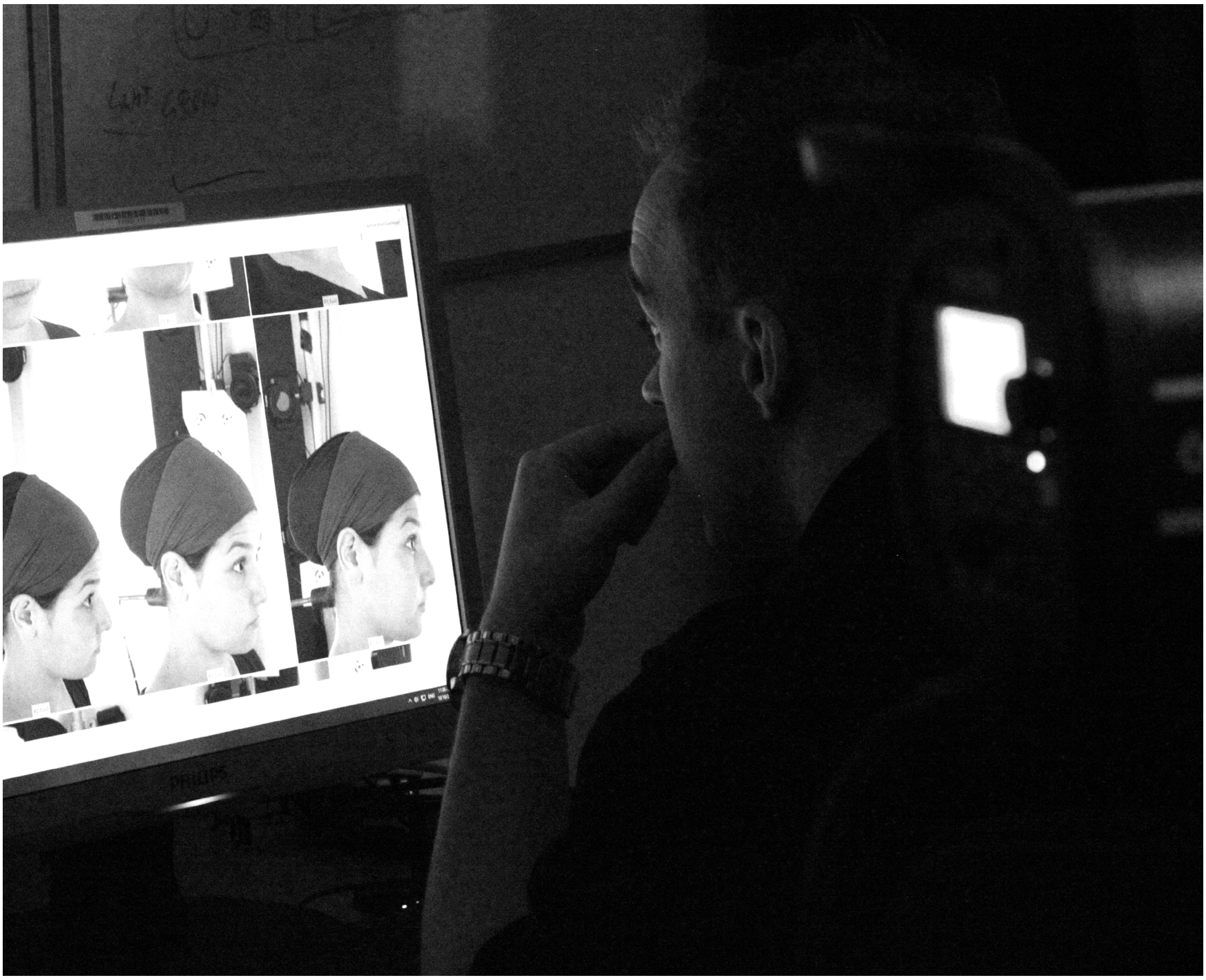

Figure 2: The researcher processing the captured photogrammetry data.

1. INTRODUCTION

1.1 Research Rationale

Over the last decade the level of realism of three-dimensional (3D), Computer Graphics (CG) has increased (Community BUFF, 2018). By applying modern techniques such as machine learning, procedural generation, artificial intelligence, and photogrammetry, new possibilities are arising for CG developers.

Photogrammetry techniques obtain reliable information about physical objects and the environment through the process of recording, measuring and interpreting photographic images (Abet et al., 2010). A more simplified description of photogrammetry would be; the generation of 3D models from multiple two-dimensional (2D) images. Specialized software can use multiple 2D images to calculate through triangulation the 3D dimensions of the object. Often the results are very good, although not perfect, and they contain errors, such as gaps of missing 2D information, or distortion in complicated shapes such as hair or transparent materials. This is where 3D artists intervene and need to clean and improve the result of the automated photogrammetry process to make it usable in a media product.

Since the study relies on the creation of specialized 3D models, some of the terminology needs to be explained. A 3D model, often also referred to as a mesh, is an object made up from a number of triangular polygons, often called faces as well. Generally, the higher the polycount, the higher the detail of the model, and the bigger the computing time. The models do not store any color information. This is done in a texture, which is a 2D image wrapped around the 3D model. Textures can influence multiple aspects of the model, such as color, specularity, metalness, and detail information. In order to move a 3D model, an artist needs to create special additions which tell the mesh how to deform. This is done by either bones or blendshapes. While the bones create a skeleton within the 3D model, which the artist can control, the blendshapes deform the model based on other meshes.

Photogrammetry is being used to capture human faces for multiple specialized fields. Medical applications, computer animation, video surveillance, teleconferencing, and virtual realities are some examples (D'Apuzzo, 2002). Although each field has a different use case, most often they all aim for a high level of realism. D'Apuzzo explains the need for high accuracy in 3D models captured by photogrammetry, which are used

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for medical purposes (D'Apuzzo, 1998). His paper presents the difficulties of facial surgical interventions, and how photogrammetry can improve the process.

In 2019, the Research and Development (R&D) team of Breda University of Applied Sciences (BUas) built a state-of-the-art photogrammetry studio (BUas, n.d.). The purpose of the specific setup of the photogrammetry studio enables the capture of high-resolution photographs of the human upper torso, focusing on the human face. A total of 33 individual cameras capture a subject simultaneously from multiple angles, after which a computer converts the photographs into a 3D model.

The purpose of the photogrammetry studio is to not only a single model, however, to capture 40 different individual models or expressions from a single person, which are called poses. These 40 individual poses are individual 3D models and afterwards connected into a single animated *base-mesh*. This generates realistic fully animated 3D avatars, which can be controlled by 3D rendering software, such as a game engine.

Now that this, and other similar photogrammetry studios, are able to capture human faces, new questions and challenges arise. This study attempts to give insights into defining how many expressions are recognizable on realistic CG human faces when compared to actual photos of the real-life human face. The study supports the R&D team who is continuously improving the photogrammetry studio, which in turn provides a basis for a better understanding of how to create a more realistic digital representation of a face, and by understanding and analysing how people recognize and perceive expressions. In detail, the experiment aims to give more insights on if, and when, to choose CG images instead of traditional photographs. Companies often need to make a choice between using photographs or CG faces, and the arguments for each choice are diverse. The decision can only be made with confidence if it is known what are the differences, and similarities, in the readability of faces in photographs when compared to CG images. This gap of knowledge, about the differences in how people perceive facial expressions, is unexplored by previous research.

When reading this study, it is important to understand the definitions of the terminology *emotions* and *expressions*, and how they are intended by the author. Emotions are mental states associated with thoughts, feelings, behavioral responses, and a degree of pleasure or displeasure (Ekman et al., 1994). As they are often intertwined with terms such as mood, personality, and motivation, and are linked with a mental state which may have physical manifestations shown through facial expressions. The formal definition of an expression is the position of the muscles beneath the skin of the face. A facial expression is a form of nonverbal communication, often to convey the emotional state of the sender (Freitas-Magalhães, 2011). Because the experiment relies heavily on visible changes and the recognition of facial poses, the experiment focuses only on facial expressions.

1.2 Research Aim

Multiple industries, like the medical, media, and videogames, aim to achieve the highest level of realism of CG images by applying modern techniques such as photogrammetry. Without human input, the results from this method provide a realistic image; however, audiences often report that it appears to be lifeless (Statham, 2018). This is why developers convert these raw CG models into optimized avatars by adjusting *shaders* and *topology* and add extra features such as hair, cavities, and animated facial expressions. During this phase, there is a high risk of a negative Uncanny Valley (UV) effect being displayed due to human error (Slijkhuis, 2017). UV postulates that a too high level of realism of avatars in VR increase the perceived "*creepiness*" of the avatar (Gisbergen et al., in press; LaValle, 2017; Mori, 1970; Seyama & Nagayama, 2007) which will be presented more in-depth in the literature review. Expressions created by developers can be perceived differently by the audience. For example, if the developer poses a CG avatar in an angry expression, the audience may perceive it differently, such as rage, jealousy, or sadness. This study assists developers in understanding if the intended expressions align with the perceived emotional states, and where the differences are between the use of photos and CG. The results of this study support the following research goal: "The between-subjects experiment aims to obtain insights into the differences and similarities of facial recognition of human expressions, in order to help the development of lifelike CG human faces".

1.3 Relevance

1.3.1 Academic Relevance: Project VIBE and BUas

The photogrammetry studio is developed for the Virtual Humans in the Brabant Economy - VIBE - project. With a consortium of 13 partners, VIBE aims to develop virtual humans for training purposes in the healthcare industry. The project monitors human communication in healthcare settings, builds virtual humans on the basis of these data, and then tests the virtual humans in similar settings. The avatars communicate with their human users via speech, facial expressions, and nonverbal behaviors in virtual, mixed, and augmented reality environments. Such interactive avatars can be deployed in several domains, particularly those domains for which interaction is critical, such as healthcare. These avatars can support the training of caregivers, or provide information to patients (VIBE, 2017). VIBE is enabled by the European Union, OPZuid, Ministry of Economic Affairs, Province of Noord-Brabant, and the Municipality of Tilburg.

Within BUas, the Academy of Games and Media (AGM) aims to create games and digital media, with a focus on engaging playful experiences in Digitally Enhanced Realities, DER. This project has high relevance with the goal of AGM. It falls under the wider theme of one of AGM research lines; *Managing and designing experiences*. AGM Research encompasses the Digital Media Concepts research line; giving insights in developing Virtual Reality, VR, concepts and media strategies that predominantly target the general public. Starting from the media context in which VR is used to measure, investigate, and understand its functionality. Measuring the effect of realism in human facial expressions expands the existing knowledge. The key question of the AGM evaluation report is; "*How to create and measure playful user experiences in virtual worlds*?" This key question tries to understand what, and how, to measure and compare experiences in virtual worlds with experiences generated via traditional media. The more technical sub-goal of the question is to create and examine the effects of high-quality worlds and characters in VR (Lappia et al., 2018).

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1.3.2 Industry Relevance

With the creation of CG representations of humans, new possibilities can be explored. In the field of media, CG is already replacing human actors. Hollywood conducted several attempts at creating CG humans, which have unique benefits. The CG actors do not age, do not negotiate contracts, and have no illnesses (Hicks, 2018). Another example is the creation of Artificial Intelligence (AI) news anchors, like Xinhua, Qiu Hao, or Zhang Zhow (Loeffler, 2019). The use of AIs allows for one anchor to present two different stories at the same time to different TVs or displays. The question of whether CG and AI can replace humans is becoming increasingly important (Elezaj, 2018). Should developers state when users are interacting with a '*fake*' human? For example, Google Assistant already sounds so lifelike, it is almost indistinguishable from a real human voice (Welch, 2018). This experiment will help to understand which expressions are obvious to the participants, and which expressions are more difficult to differentiate. Developers can use these results to make a substantiated choice in when to use photographs or realistic CG humans. Traditional photographs have the advantage of fast and highly realistic results. However, CG allows for customization on a completely new level, such as zoom, animations, or the manipulation of expressions. Images can be altered years later, without the need of having the actor there, and extreme and unrealistic situations can become reality, nonetheless, the technique is currently expensive when compared to modern photography. A reason to choose one over the other might be the different effects they have on the ability of audiences to recognize human expressions, and that is the gap this study seeks to address with this experiment.

1. INTRODUCTION

1.4 Thesis Outline

The first chapter of this thesis gives an introduction to the research problem and question, and the academic and industry value of this experiment.

The second chapter presents the literature review and the theoretical framework of this study. The first section explores the knowledge gap of the already existing research. Followed by a section that introduces the technology which is needed to create CG faces. The between-subjects experiment relies on realism, created by a method called photogrammetry. In the next section, the field of recognition of expressions is described, in order to understand how expressions can be applied to artificial faces and to gain insights on how to measure them. After that, the Uncanny Valley effect is presented, which explores what makes an artificial face appear to be real. Followed by the Facial Action Coding System, and how this theory is used within the field of media.

The third chapter outlines the quantitative research method. A description of the study's research procedure, material, and equipment, used can be found in this chapter, followed by an overview of the demographic data of the participants. The conceptual framework is presented, which is the Multimodal Emotion Recognition Test and the Wheel of Emotions by Plutchik, followed by the method of data analysis. The chapter ends with reflections about possible ethical issues.

Chapter four presents the findings. First, the results and the statistical analysis of the two groups of the experiment are presented, focusing on the similarities and differences. Afterwards, the results of the recognition of the individual expressions are presented. Followed by a comparison of the Big Six and the Secondary Expressions. Next, the influence of the actors are presented, to establish if there is a difference between the two. Lastly, the chapter ends with the findings of the intensity levels of the expressions.

The fifth chapter contains a discussion based on the findings in chapter four. The chapter provides a hypothesis for the obtained results in chapter four.

The sixth and last chapter outlines the contribution of the knowledge obtained by this study and provides recommendations for the application of the results. Afterwards, its limitations are presented. Lastly, suggestions for further research are enumerated.

2. LITERATURE REVIEW

This chapter reviews relevant literature, establishing the theoretical foundation for the research question, and critically reflects on the presented literature. First, the knowledge gap in existing research is explored. Followed by an overview of the modern photogrammetry techniques. Then, the methods of the recognition of expressions are discussed. Additionally, the Uncanny Valley effect will be reviewed, followed by the Facial Action Coding System.

2.1 Exploring the Knowledge Gap

Multiple studies have been conducted regarding the recognition of expressions, or emotions. However, there has not been a comparison between the recognition of facial expressions in photographs and CG images. An experiment named Interpreting Human and Avatar Facial Expressions, by Noël et al., has a very similar approach to the experiment in this study (Noël et al., 2009). The experiment compares humans versus avatars and utilizes seven similar expressions, which are explained more in-depth in section 3.5.2. The images are based on a method named FACS, which can be found in section 2.5. The experiment by Noël et al. took place in 2009, with avatars that are from a low quality compared to modern standards. Figure 3 shows the difference in quality between the avatars used in the experiment of Noël et al, and the CG images created for this study.

Other studies have been conducting similar research experiments, however, they focused on different variables; for example these variables are, experiencing, liking, presence, or naturalness (Gisbergen et al., in press). A research paper named, The Effect of Realism in Virtual Reality on Experience and Behaviour, by van der Heeft et al., explains the different definitions of realism (Heeft, 2019). The definition of realism which applies to this study refers to resemblance, in which realism is used to reproduce something that is familiar to the participants. Section 2.4 explores the understanding of realism and possible downsides of developing CG images of human faces in more detail.

Research states that highly realistic characters raise higher expectations of the users, which can lead to disappointment if these expectations cannot be met by providing a consistently high level of realism (Garau et al., 2003; Slater & Steed, 2002; Van den Boom et al., 2015). With modern technology rapidly increasing computing power, the expectation of realism is higher than ever (Stuart, 2015; Kim, 2014). This is where the between-subjects experiment of this study may provide new insights by implementing state of the art capturing techniques.

2. LITERATURE REVIEW

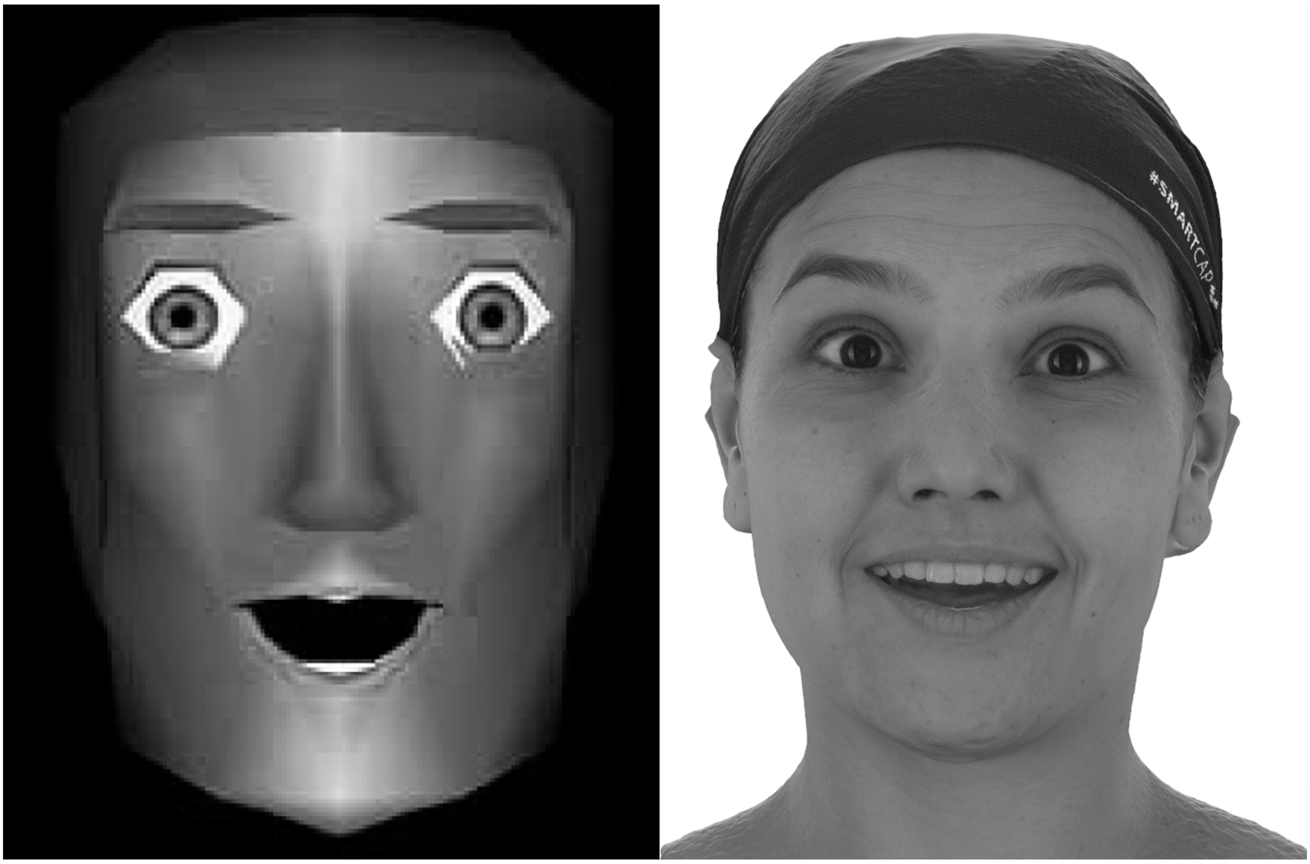

Figure 3: On the left; a CG avatar used by other experiments. On the right: the CG image used by this experiment.

2. LITERATURE REVIEW

2.2 Capturing Human Expressions with Photogrammetry

Since this study compares photographs with CG images, it is important to understand how to capture human faces and convert them into 3D models. To gain a better insight into the technique, this section presents the method, history, and the application of photogrammetry in video games and serious applications.

2.2.1 Photogrammetry

As explained in the previous chapter, photogrammetry encompasses methods of image measurement and interpretation in order to derive the shape and location of an object from one or more photographs of that object. The main purpose of photogrammetric measurement is the 3D reconstruction of an object in digital form (Luhmann et al, 2013). The method gathers quantitative data and is traditionally a part of geodesy science, belonging to the field of remote sensing. To obtain 3D data out of a 2D image, the third coordinate needs to be located. To do so, a technique called *stereoscopic viewing* is used to obtain the 3D information in photogrammetry, depicted in Figure 4. The technique has similarities to the way human vision works; the distance between the eyes creates an overlap which enables to perceive depth. Overlapping photographs allow for photogrammetry to calculate depth. If two or more photographs are taken from the same object from different positions, a third dimension can be calculated by comparing the same points on both of the photographs (Linder, 2014).

Figure 4: A CG face generated trough photogrammetry by using 33 photos captured from different angles.

2. LITERATURE REVIEW

2.2.2 History of Photogrammetry

The method of photogrammetry is already an old concept and applied in many different fields. In 1981, Ghosh wrote a paper about the history of photogrammetry. It describes how in 1921 Reinhard Hugershaff introduced the Autocartograph, the first universal photogrammetric platter (Ghosh, 1981). Inspiring others, different versions and applications followed (The Center of Photogrammetric Training, n.d.). In between the two World Wars, photogrammetry became a method of mapping big areas by using air balloons. After the Second World War, the technique became widely available as a result of economic growth. Other fields, such as archaeology, topology, civil engineering, and automotive adapted this method to their specific needs (Dessler, 2018).

2.2.3 Photogrammetry and Video Games

Since 2011, when *L.A. Noire* was released, photogrammetry has been adopted as a popular method for creating complex 3D models (Stamoulis, 2016). Before 2014, the technique was discarded for being too cumbersome and game engines were too limited. However, the developers of *The Vanishing of Ethan Carter* proved that the technique is able to create highly detailed environments. Shortly after in 2015, EA DICE used photogrammetry for the creation of props, clothing, and settings of *Star Wars Battlefront*. From that point onwards the games industry has been investing into the research of the creation of photogrammetry assets and software (Statham, 2018), including the appearance of several companies where photogrammetry is their core business. Thus, the understanding of how audiences actually perceive human facial expressions becomes more important. Especially for video games it is important to comprehend which expressions translate well to CG faces, and which do not.

Figure 5: Different applications of photogrammetry in video games. From left to right: *L.A. Noire, The Vanishing of Ethan Carter, Star Wars Battlefront.*

2. LITERATURE REVIEW

2.2.4 Photogrammetry and Serious Applications

The photogrammetry technique is not only being used for games; also serious applications benefit from this solution. According to Chong, the method has been used for a broad variety of medical applications (Chong, 2009). Of these, craniofacial, human trunk, extremity, wounds, and dental mapping are the most common. The paper describes a futuristic outlook and concludes that the future of photogrammetry is bright even though, at the time, the technique was still limited. According to Patias, photogrammetry has gained popularity as a method of repeatable reproduction of body structures for the planning and monitoring of therapeutic treatment and its results (Patias, 2002). Ey-Chmielewska et al., conclude that modern digital image processing methods, such as photogrammetry, allow the high reproducibility and objectivity of results. 'The technique has strong competition for other previously used methods. Photogrammetry allows for the recording and comparative assessment of various phenomena in human tissues. Other use cases would be the possibility of adopting common standards for data and image archiving. The patient data can be easily compressed, transferred, and encoded' (Ey-Chmielewska et al., 2015).

2. LITERATURE REVIEW

2.3 The Recognition of Expressions in Human Faces

There is an extensive amount of literature available on the recognition of signs that indicate expressions, both within the psychological tradition and beyond it. Research states that human facial expressions consist of three categories (Liong et al., 2016). The first category concerns the macro expressions, which are visible for 0.5 to 4 seconds and are obvious to the eye. The second category is the so-called micro-expressions, which are visible for less than half a second, and mostly happen when trying to conceal the current facial expression. The third category is the subtle expressions, which are associated with the intensity and depth of the underlying macro and micro expressions, and almost invisible to the human eye.

The most common limitations that arise when humans try to read and define an expression can be summarized in three categories (Ekman, 2003). The first category concerns the display and social rules, Ekman and Friesen stressed the universal underpinnings of facial expression and the variety within cultural rules. Unrestrained expressions of anger or grief are strongly discouraged in most cultures and may be replaced by an attempted smile rather than a neutral expression (Ekman & Friesen, 1969). The second category is deception. There is a fine line between the display rules and deception categories. Deliberately misrepresenting emotional states is manifestly part of social life, which can be difficult to spot. The third category is called systematic ambiguity, which are the signs relevant to expressions that may have alternative meanings. For example, lowered eyebrows may signify concentration as well as anger. Other examples are less obvious, such as the strong similarities between the characteristics associated with depression (Nilsonne, 1988) and those associated with a person having difficulty while reading (Cowie et al., 1999). The recognition of expressions proves to be difficult. Research show that people have the ability to recognize the macro expressions, however, the micro or subtle expressions are more difficult. Matsumoto and Hwang stated that the average accuracy of correct recognition rate was 48% in their study. When excluding the two easiest expressions to recognize, joy and surprise, the accuracy rate drops to 35% (Matsumo & Hwang, 2011). Others have similar results. Qu et al. studied the awareness of facial micro-expressions and macro-expressions. They found awareness rates of 57.8% (Qu et al., 2017).

2. LITERATURE REVIEW

2.4 Defining Realism in CG Faces: The Uncanny Valley Effect

The definition of the Uncanny Valley (UV) hypothesis by Masahiro Mori in 1970, states that humanlike artificial characters which are almost, however not fully, realistic trigger a sense of unease among their viewers (Valley et al., 1970). Over the last 40 years, the hypothesis has become widely accepted and gained high popularity in the field of media and scientific research (Kätsyri et al., 2015). Over time, significant differences between the various versions of the UV are being used in literature (Slijkhuis, 2017). The term Uncanny Valley refers to a graph of emotional reaction against the similarity of a robot to human appearance and movement, as shown in Figure 6. The theory describes how viewers have a greater affinity for CG images that are more realistic. The viewers affinity increases as the CG images become increasingly realistic, until the illusion breaks. The semi-realistic zone of the graph shows a dramatic drop because the CG images trigger unease in the viewers. Looking at the graph, there comes a point where the valley has been crossed, and the affinity of the viewer reaches the highest point. Thus, 'crossing the UV' has been a significant hurdle in the creation of perceptually realistic CG faces (Seymour et al., 2019).

One of the difficulties in applying the original UV theory is that there is a difficulty in measuring affinity. It is not a dependent variable against which one can test with some independent variables. Affinity is currently the accepted translation of the Japanese word Shinwakan (親和感), which was used in the original article. In the past, other English translations have been used to describe the UV vertical axis, such as familiarity, rapport, and comfort level (Ho & Macdorman, 2010). According to academic literature, proper research is still needed to determine if the phenomenon exists (Brenton et al., n.d.). Brenton argues that the higher the level of realism, the higher the expectations for motion and behavior become, which forces the movement and animations to be of the same realistic level. Keeping the limited time scope to conduct the experiment in this study in mind, and to minimize the high expectations which trigger the negative UV effect, this thesis only focuses on photographs and still CG images.

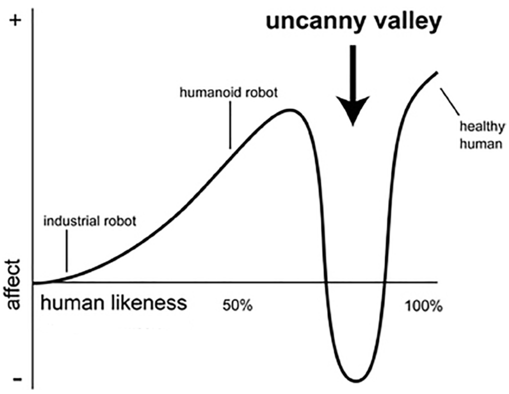

Figure 6: The Uncanny Valley curve which compares the likeness versus the affect of artificial faces.

2. LITERATURE REVIEW

2.5 Controlling a CG Face: The Facial Action Coding System

One of the most established expression models is the Facial Action Coding System, FACS, from 1970 (Facial Expression Analysis The Complete Pocket Guide, n.d.). The between-subjects experiment presented within this study is based upon the original FACS experiments from 1970 and 2002, shown in Figure 7. The original FACS experiments established a system which taxonomizes human facial movements, and the expressions these movements create. Later the movements of individual facial muscles were encoded. FACS became the common standard to systematically categorize physical expressions (Hamm et al., 2011). The original experiments contain black and white images, focusing on all muscular expressions possible by a human face. As an addition, the between-subjects experiment in this study takes non-muscular color changes, such as blushing, into account.

The FACS method is originally created by Hjortsjö with 23 facial motion units in 1970, it was subsequently developed further by Ekman and Friesen (Ekman, & Friesen, 1969). The FACS as we know it today was first published in 1978 and was substantially updated in 2002 (Ekman & Rosenberg, 1997). The FACS approach represents a fully standardized classification system of facial expressions for expert human coders based on anatomical features. Experts carefully examine imagery of faces and describe any occurrence of facial expressions as combinations of elementary components called Action Units, AUs (Ekman et al., 2002). Each AU corresponds to an individual face muscle or muscle group and is identified by a number. All facial expressions can be broken down into their constituent AUs. Assumed that facial expressions are words, AUs are the letters that make up those words (Ekman et al., 2002).

The system has been widely accepted and used in different fields. Den Uyl and van Kuilenburg based their FaceReader system on the original FACS and applied it in a security and medical context (FaceReaderTM, n.d.). Their system looks for facial signals to identify when specific mental processes are occurring (Uyl & Kuilenberg, 2005). FACS gained popularity within the Visual Effects and Gaming industry. For God of War, Santa Monica Studio based their photogrammetry scans and blendshapes on the established FACS research. Industry-wide tools are being developed to control and combine individual 3D scans since the additive nature of 3D software causes new challenges which the pre-gaming-era FACS did not take into account (Thacker, 2018).

2. LITERATURE REVIEW

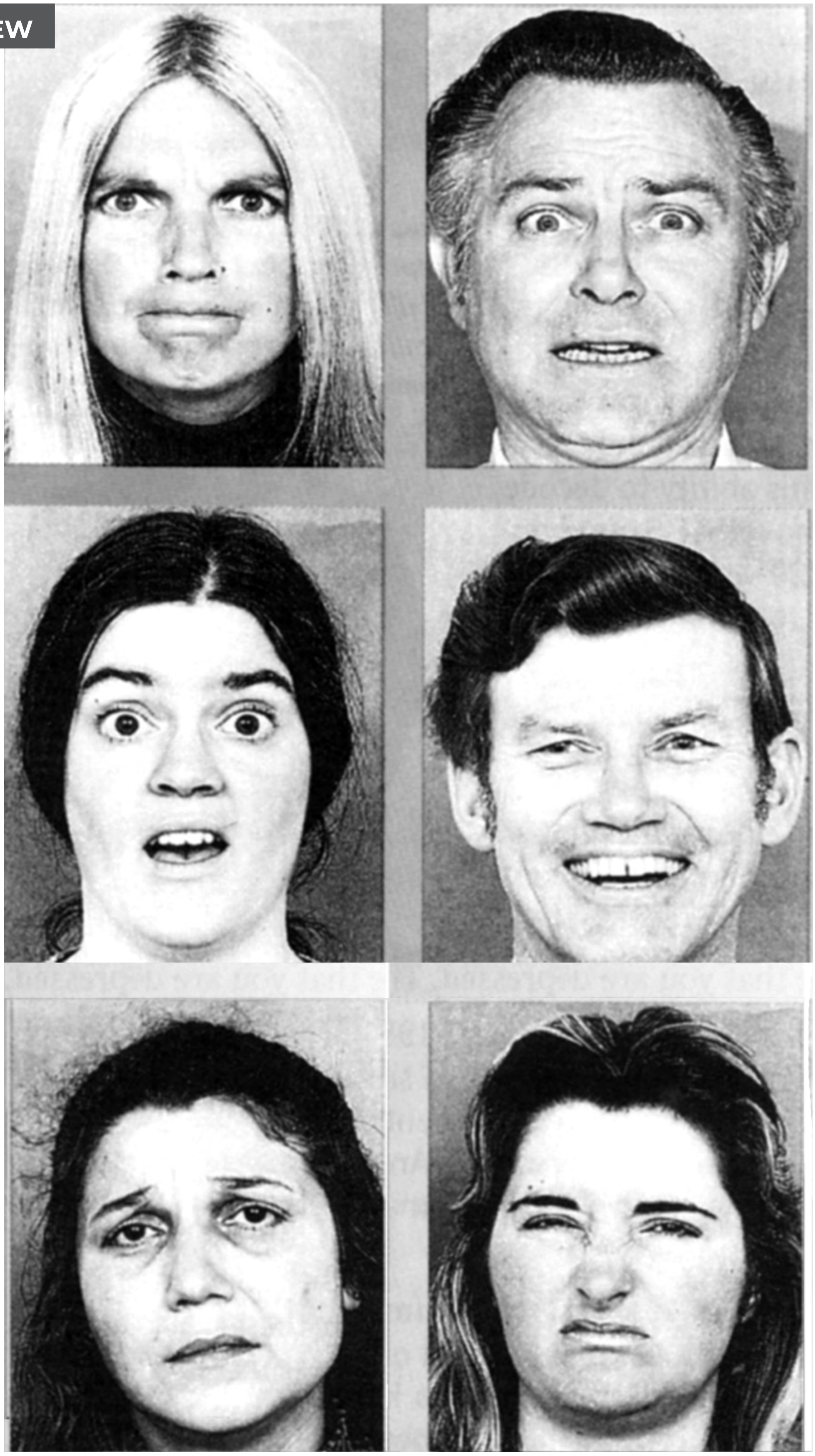

Figure 7: Photos of different facial expressions of the original FACS test.

2. LITERATURE REVIEW

2.6 Wheel of Emotions by Plutchik

An established researcher within the field of emotion recognition is Plutchik. Together with Whissel he created a table called Emotion Words, which can be used with Plutchik's Wheel of Emotions, shown in Figure 8. The wheel contains eight primary emotions that Plutchik identified, which are the basis for all expressions and are grouped into polar opposites: joy and sadness, acceptance and disgust, fear and anger, surprise and anticipation (Cowie et al., 2001). From here, the secondary and tertiary emotions spawn. The emotion wheel is a valuable base to develop experiments related to expressions and emotional states.

The emotions depicted in this model are often split between the expressions which are known, and the ones that should be learned. The expressions humans already know are often referred to as the Big Six, used in Paul Ekman his research on the pancultural recognition of emotional expressions (Ekman et al. 1969). The Big Six expressions are happiness, sadness, fear, surprise, anger, and disgust. While there is disagreement which other expressions should be added to the Big Six among researchers, these six have become widely accepted (Prinz, 2004). Other expressions need to be learned in order to be able to recognize them. They contain admiration, adoration, aesthetic appreciation, amusement, anxiety, awe, awkwardness, boredom, calmness, confusion, contempt, craving, empathic pain, entrancement, excitement, horror, interest, joy, nostalgia, relief, romance, satisfaction and sexual desire, and are identified by researchers associated with the University of California, Berkeley (News Staff, 2017).

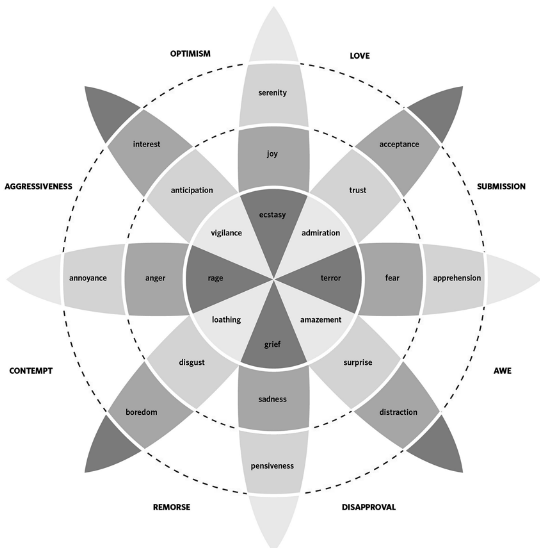

Figure 8: The Plutchik wheel of emotions.

3. METHODOLOGY

3.1 Research Perspective

The literature reveals the difficulty of capturing human faces in CG and applying convincing facial expressions to 3D models. Now, with modern capturing techniques, high quality of CG images can be achieved. This study researched whether there is the same level of recognition of human facial expressions between the traditional photographs, and the high quality still CG images. This chapter focuses on the methodology of the experiment. It provides an overview of the research perspective and applied methods. Furthermore, the materials and equipment are presented in detail. Additionally, the selection of participants and the sampling method are explained followed by the procedure of the data collection and analysis. Finally, the ethical considerations regarding the participants and actors taking part in the experiment are presented.

As discussed before, this study is part of the VIBE project, which aims to create detailed CG humans for medical training purposes. The experiment aimed to measure the difference in perceiving expressions between photographs and CG images taken with a photogrammetry method, providing the 3D artists of BUas insights on recognizing facial expressions.

3.2 Design

This study was based on experimental design, applying a in-between participant experiment. Two individual groups were tasked to recognize human facial expressions. All participants, of both groups, would receive the same tasks, in the same order, with the same actor performing a specific expression. The expression was displayed for exactly for two seconds, before the participants were required to select one of ten possible answers. The only difference between the groups was the displayed format. Group Photographs assessed still photographs, while group CG saw CG images captured by a photogrammetry rig. Individual datasets for both groups with regard to participant choices were collected and compared using Qualtrics (Qualtrics XM, n.d.). The R&D team of BUas developed a custom JavaScript that supported this experiment. The JavaScript code allowed the researcher to set a display time limit for which the images were visible, within Qualtrics.

3. METHODOLOGY

Figure 9: Screenshots illustrating the different versions of the experiment side by side. Photographs (A) versus CG images (B).

3.3 Procedure

3.3.1 Data Collection

The participants invited to participate in the experiment as an online rating study. The study was based on the established MERT experiment, replicating the MERT user manual (Bänziger et al., 2009). Each test started with an Informed Consent, see Appendix 2, where an explanation of the experiment was given. When the participant started the study, an example question appeared, allowing the participant to test if the experiment ran on their device. The example question gave the participant a feel for the timing of the photos and the possible answers.

During the trial and testing phase of the questionnaire, and before the actual study took place, the testers warned the researcher that the English translation of the expressions could cause confusion among the Dutch participants. Since the participants were gathered through mostly convenience sampling, and a large portion of the participants were native Dutch speakers (75% of the participants). An extra section was added to the study to translate the expressions, in order to avoid confusion.

Test A contained only photographs of both male and female actors representing different expressions. Participants were shown ten options per photo, with 40 photos in total. The B version contained the same information, however, instead of photos, the experiment displayed 3D CG models captured by a photogrammetry rig. The order of the photos and images was in the same sequence while making sure the same expression was not displayed twice in a row. Each photograph and CG model was displayed for two seconds, based on the MERT experiment. This allowed participants to only give their first impression, without overthinking their answer. Each experiment ended with demographic questions regarding the participant information. The first set of questions asked participant information, such as gender, age, location, and level of education. The second set questioned the participants about their ability to read expressions and the difficulty level of the experiment. To understand if participants were familiar with CG generated faces already, the participants were asked how frequently they watch VFX movies and play videogames. To ensure participants were not biased, the last set of questions checked if participants know any of the actors shown. The final question allows participants to leave feedback, tips or comments.

3. METHODOLOGY

3.3.2 Data Analysis

To analyze the data, the statistical program IBM SPSS 26 and Office Excel were used. First, the data was filtered from Qualtrics, removing empty or incomplete questionnaires. After export, the data was ensured to be clean and free of errors. Next, the data was collected in a master Excel file, to give a clear overview of all the gathered data. This file can be found in Appendix 4. Hereafter the data was split into smaller Excel files to measure the different means for the different sub-hypotheses in SPSS. The data got divided into individual questions regarding the intended expressions, and into expression families. These families combined the ten expressions into five expression families, to check if there was a difference in the results. Additional, two Independent Samples t-tests checked the P-values of these two groups; the individual questions, and the families. Before applying the t-tests, a check of the right division of the normal curve took place, to make sure the t-test was the right statistical analysis for this data.

3.4 Participants

One hundred participants, 57 women, 42 men and 1 not specified, took part in this study. 43% of the participants was between the age of 18 - 24. Followed by 40% of the group from 25-34, and 14% was between 35 - 44 years of age. The last group, 3%, was between 45 - 54 years old. The experiment used both random sampling and convenience sampling. Due to the nature of the experiment, having a wide diversity of participants helped the researcher in understanding how different people recognized facial expressions. Therefore, random sampling allowed for everyone having an equal chance of being selected as a participant. The convenience sampling comes forth from the accessibility of the participants to the researcher. During the selection of the participants, the main constraint was the guarantee of not having CG developers and experts in the participant pool. To ensure both experiments had the same number of participants, in the end, both tests are connected to an application called Splitter. Splitter sends participants to either the A or B experiment with one single link, controlling the division of the participants (AppDrag, n.d.).

3. METHODOLOGY

3.5 Measurements

In 2009 Banziger, Grandjean, and Scherer developed an instrument that objectively measures the ability of emotion recognition, named Multimodal Emotion Recognition Test, MERT (Bänziger et al., 2009). This instrument is originally used for still pictures, audio/video, audio-only, and video only. To develop MERT, 12 professional stage actors were tasked to display a certain expression. No actor was used twice for the same expression category to decrease the possibility of associating a specific actor with an expression set. The original test, from which MERT was developed, contained 14 facial expressions.
Six of the fourteen facial expressions are part of the core expressions, known by the Big Six: happiness, sadness, fear, surprise, anger, and disgust. Besides the selection of the Big Six, interest, boredom, shame, pride, disgust, and contempt were also are included. Some of those expressions are displayed at different intensity and arousal levels. For example, the anger category contained; hot anger and cold anger, the fear category contained; panic fear, and anxiety, the sadness category contained; despair and sadness, and the happiness category contained; elated joy and happiness.

Besides the selection of the Big Six, interest, boredom, shame, pride, disgust, and contempt are included. For the video and the audio recordings the actors were tasked to speak meaningless two sentences: “Hat sandig pron you venzy” and “Fee gott laich jonkill gosterr”. These meaningless sentences resemble normal speech, however do not mean anything, to make sure the content did not influence the participants (Scherer, Banse, Wallbott, & Goldbeck, 1991).

Out of a database of 224 recordings, which were selected by acting students, MERT randomly selected 30 recordings with different criteria. During the test, the expressions were displayed in a random order, making sure the same actor or expression was not displayed twice in a row. The answers from participants had to be given in an application, where they were given a forced choice. Every expression was displayed for two seconds, and participants were tasked to select one of four categories. With the MERT method being ten years old, CG captured images by a photogrammetry technique

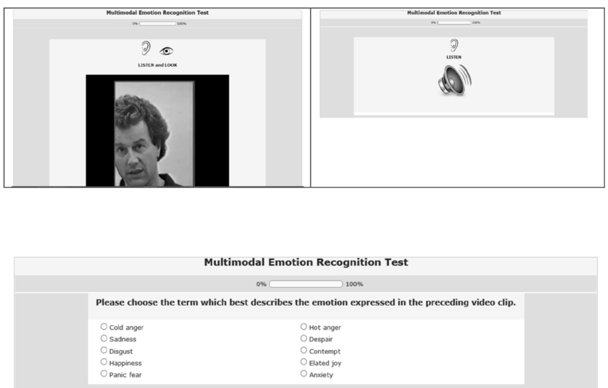

Figure 10: Screenshots illustrating the original MERT test for an audiovisual and an audio item.

has not been measured yet using the MERT method. Replicating the MERT procedure of measuring still pictures and applying it to CG images presented new insights into the established method.

3.6 Material

The experiment consists of ten facial expressions of two actors, male and female, with two intensity levels for each of the following ten expressions: irritation, hot anger, sadness, despair, disgust, contempt, happiness, elated joy, panic fear, and anxiety. These ten expressions are based on the Plutchik Wheel of Emotions. The still pictures and photogrammetry CG scans combined yield a total of 80 items. Appendix 1 displays the questionnaire used for this experiment.

3.6.1 Photogrammetry Studio

BUas has been developing a photogrammetry studio since the start of 2019. While adjustments and additions were still being made, the studio was ready to be used for the first research experiments.

The photogrammetry studio contained 33 Canon 2000D cameras, each camera was equipped with a 50 mm f/1.8 lens, polarizer lens, and camera hood. With over a hundred meters of network cables the cameras were connected to 34 Raspberry Pi's 3 B+ which collected the photos from each individual camera and send them over a network switch to five servers, where the photos were converted into 3D models. The four Godox QT600II M lights provided up to 2400 Watt of light, canceling out all the possible shadows from each direction. The studio generated 30 blendshapes per human facial scan. These blendshapes were automatically connected to a base rig, which was controllable within the Unreal Engine 4 game engine (Unreal Engine, n.d.). An external custom application programming interface, API, allows to command and steer the facial expression.

3.6.2. Actors

Two actors have been selected, a male and a female. To prevent any failures due to technical difficulties, another two shoots with back up actors were recorded. The female actress is a certified actress, dancer, and coach. She guided the display of the expressions to guarantee the believability of the expression made by all the actors.

3. METHODOLOGY

3.7 Analysis

For each displayed expression three variables were presented in the test. The first variable indicated which format was presented to the participant: a still picture or a 3D CG model was presented. This was indicated in the first part of the variable name; SP for the still picture category, CG indicates that the images were captured by a photogrammetry technique. The second part of the variable name started with a number indicating the intensity level of the displayed expression, ranging from one to two, with two being the highest level. The third letter indicated which expression was showed, for example, A for anxiety. Table 1, which can be found in the Appendix 1, clarify and support the deduction of which expressions the letters represent. The last letter showed the sex of the actor showed to the participant, F for female, M for male. For a complete overview of all the variables see the Appendix 1, Table 2. An example of a variable name would be SP1AM.

The participant results are summarized by adding two extra variables; the first new added variable is the expression selected by the respondent, for example, SP1AM-K. The other variable indicated whether the given answer is correct, 1 for being correct; 0 for being wrong. An example of the final outcome is SP1AM-K-0. At the end of the file, sum scores are calculated for each format as well as a total score for the whole test, expressed in a percentage of correct answers. For convenience, the between-subjects test took place in an online environment, which allowed the participants to join at any location without the researcher being present. QualtricsXM, which is an experience management platform, allowed the researcher to create surveys and generate reports without having any previous programming knowledge (Qualtrics XM, n.d.).

Figure 11: The photogrammetry studio used for capturing the CG images.

3. METHODOLOGY

3.8 Ethical Considerations

In this study, a number of considerations were taken into account regarding the subject of ethics. The following paragraph divides the considerations in three categories. First it presents the overarching considerations regarding using CG humans instead of actual humans. Followed by the considerations for the actors who helped to create the experiment, and the participants following the experiment.

3.8.1 Overarching Considerations

Digitally created humans can be frightening to an audience. There are different media stories out there, such as Sci-Fi movies, which use the rise of AI as a negative event (Bland, 2019). Since there are almost no rules or regulations yet for the creation and use of CG avatars, this can be perceived as frightening. An example of a hyper realistic CG avatar is Siren (Fleming, 2017). She is a digital copy of a human, and the differences are hard to spot. When a digital copy has been created, they can be controlled on different platforms, and controlled by anyone or an AI, without the input of the actual human the copy was made from. These digital copies are able to do a humans job, or even replace them. Christine Marazona, a former model, started a tech company and created an avatar of herself (DNABlock, n.d.). Now her digital twin is being hired by big companies for online marketing purposes. A consideration is the appearance of these avatars. The industries of games, movies, fashion and porn are already known for the commodification of the female body. Does the technique of turning women into digital objects make this even worse, with a lot of the developers being male. Without regulations, the digital avatars could perform online actions which are normally illegal, for example in porn applications (BBC, 2019).

Participants helping in the research of CG humans might not want to participate when they understand the possible applications of the technique. Therefore, the researcher needed to consider if the participants need to be aware of when and why they are looking at a 'fake' CG face. Another consideration is the fact that the participants were already accustomed to looking at photographs, while CG expressions were less familiar for them, and therefore it might have been harder to recognize expressions. If the results showed a big difference in the recognition between the two tests, the researcher needed to establish if there was a negative UV effect present.

3. METHODOLOGY

3.8.2 Considerations of Actors

Before entering the photogrammetry facial scanning studio, clear information of the process and results are provided. BUas required the actors to sign a consent form named the Photogrammetry Rig Release Form, see Appendix 3 to safeguard both parties. The form allowed BUas to use the likeness, image, appearance, and expressions recorded by the photogrammetry studio to be made part of production for research and education by BUas. The actors were informed that BUas had complete ownership of the products the actor might appear in, as well as the copyright interests. The images could be used for marketing purposes for internal use, for educational purposes, or for closed-circuit exhibition. Lastly, the actors had to confirm they understand the agreement by signing off with their names, phone number, email address, signature and date. The form was sent out to the actors before accepting their participation in this experiment, to ensure the actors were aware of the stated agreements.

To avoid other ethical issues the actors had to be adults above the age of 18. The photogrammetry studio had a small risk of triggering an epileptic seizure due to the quick flashing lights and camera shutters. Actors could not have a history with epileptic attacks due to this reason.

3.8.3 Considerations of Participants

Before the participants could take part in the experiment, they were asked to sign a digital consent form which stated, among others, that their personal details will remain confidential and that the study was entirely voluntary. In addition, the participants were informed that a withdrawal of the study would be possible at any time and were also presented with the contact details of the researcher. An image of the digital consent form can be found in Appendix 2. A consideration to take into account was the application of the results. Did the participants want to participate in creating highly realistic digital humans? The applications ranged from video games to medical staff training and could be perceived as a frightening purpose.

Figure 12: Siren, a highly realistic digital character.

4. FINDINGS

In this chapter, the results of the study are presented. First, the similarities of the background of the Group Photographs and the Group CG are explored. Afterwards, the recognition of the intended expressions is presented. Followed by the results of the comparison between the Big Six and the Secondary Expressions. In addition, the influence of the actors is presented, followed by differences in the intensity levels of the displayed expressions.

Before reading this chapter, it is important to understand that the data within this chapter related to expressions has been studied twice. The first pass took the data of the individual expressions into account. Participants could either score a right or wrong answer, which presented a hard result. During the study the researcher received feedback from the participants such as "*...the hard ones were somewhere between contempt, irritation, anxiety and sometimes sadness or even disgust, which can all look similar to me depending on context.*" and *"...there was some overlap between the negative emotions such as disgust and contempt"*. Since some expressions have similarities and resemblances, especially comparing the Big Six and Secondary Expressions, for the second pass the expressions were combined into their respective families. These families are Happiness and Elated Joy, Panic Fear and Anxiety, Despair and Sadness, Irritation and Hot Anger, and Disgust and Contempt. Combining these families presented different results, although the data was more flexible compared to the individual expressions.

In the Appendix, a full overview of the collected results can be found. The data has been divided over a number of tables, to enhance the readability. Appendix 4 displays the relevant data output regarding all the given answers by the participants. Appendix 4, Table 1 shows all expressions with the given answers, divided into photographs and CG images. The table also displays the different intensity levels of the expressions and the given answers. Table 2, in Appendix 4, summarizes the results from Table 1 and displays the difference between the results of the recognition of still photographs and the CG images. Table 3 combines the ten expressions into five families. Table 4 summarizes the results from Table 3 and displays the difference between the results of the recognition of the correct expression families. All the statistical tables from SPSS can be found in Appendix 5.

4. FINDINGS

4.1 Group Similarities

Both of the groups showed no statistical significant difference in gender, between 54% and 60% of the participants were female (χ2(1, N=100), p = 0.545, two-tailed). The Chi-Square Test of the distribution of gender of the groups is presented in Table 1.

Gender * Group Crosstabulation

		Group		
		SP	GR	Total
Gender	Female	27	30	57
	Male	23	20	43
Total		50	50	100

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	,367[a]	1	,545

Table 1: The Chi-Square of the distribution of the genders of the participants between both groups.

Also, no significant age differences (F(0.935) p = 0.427) were found; the mean age result for Group Photographs was 27, and Group CG had a mean age result of 29. Figure 13 presents a column graph of the distribution of age between the groups.

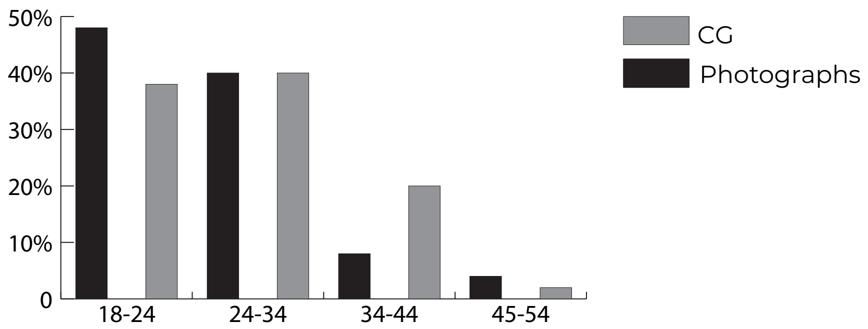

Figure 13: The distribution of participants based on age, between the two groups.

The level of education was equally divided between both of the groups (χ2(6, N=100) = 2.3 p = .604, two-tailed). Figure 14 presents the distribution of the level of education between the two groups.

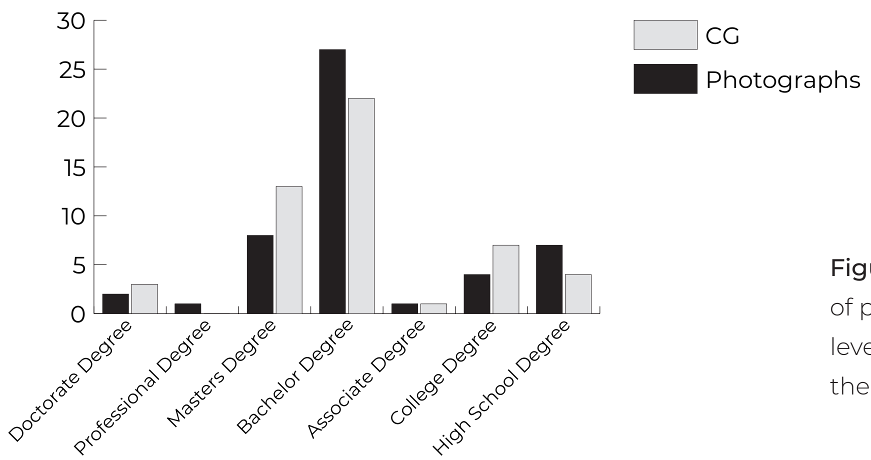

Figure 14: The distribution of participants based on level of education, between the two groups.

4. FINDINGS

The locations of the participants were diverse. The largest subgroup of the participants were based in the Netherlands (76%), followed by Germany and the USA (both 4%). The remaining participants were located in China, Czech Republic, Denmark, Italy, Malaysia, New Zealand, Philippines, South Korea, Spain, Thailand, and the United Kingdom.

To determine if participants had prior experience with viewing and perceiving facial expressions on CG avatars, the participants were asked how often they watched movies with VFX, and how often they played video games.

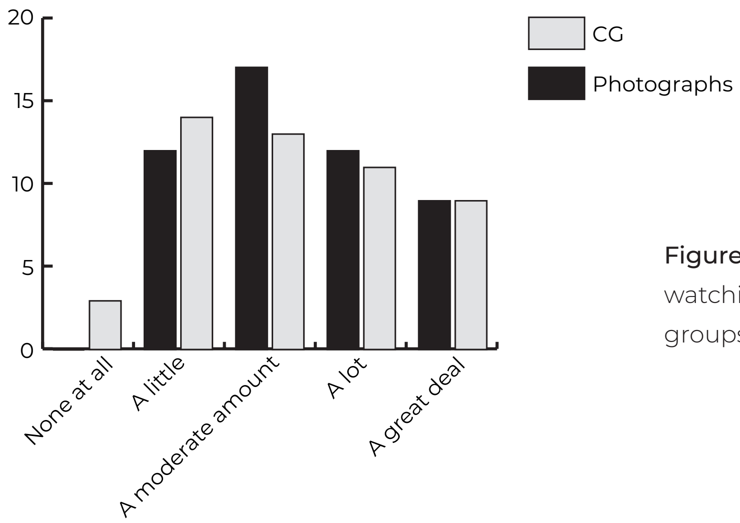

Figure 15: The distribution of participants watching VFX movies, between the two groups.

The frequency of how often VFX movies were watched by the participants are shown in Figure 15 ($\chi 2(4, N=100) = 3.731$, $p = 0.444$, two-tailed). The question regarding how often participants played video games scored differently ($\chi 2(4, N=100) = 2.940$, $p = 0.568$, two-tailed). Figure 16 presents the results for both groups.

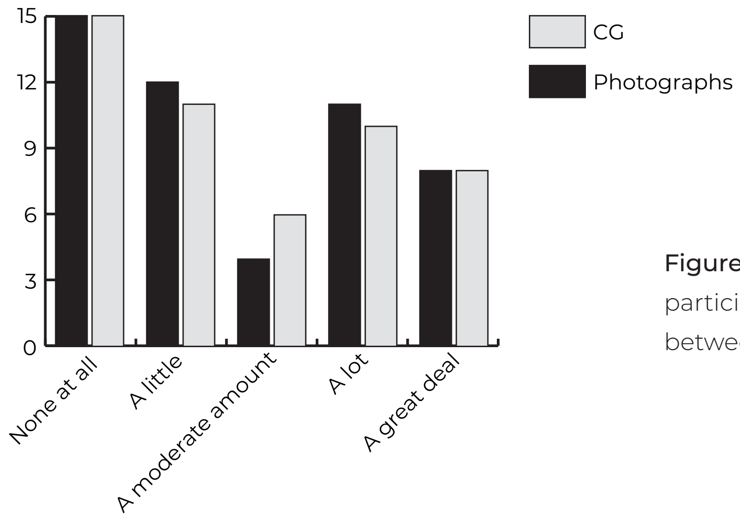

Figure 16: The distribution of participants playing video games, between the two groups.

4. FINDINGS

In addition, the participants were asked how well they can read facial expressions. The participants could rate their ability to recognize an expression on a Likert scale from extremely well to not well at all. The groups showed no significant difference in the ability to read expressions ($\chi 2(4, N=100) = 0.106$, $p = 0.891$, two-tailed). Figure 17 shows the distribution of the results.

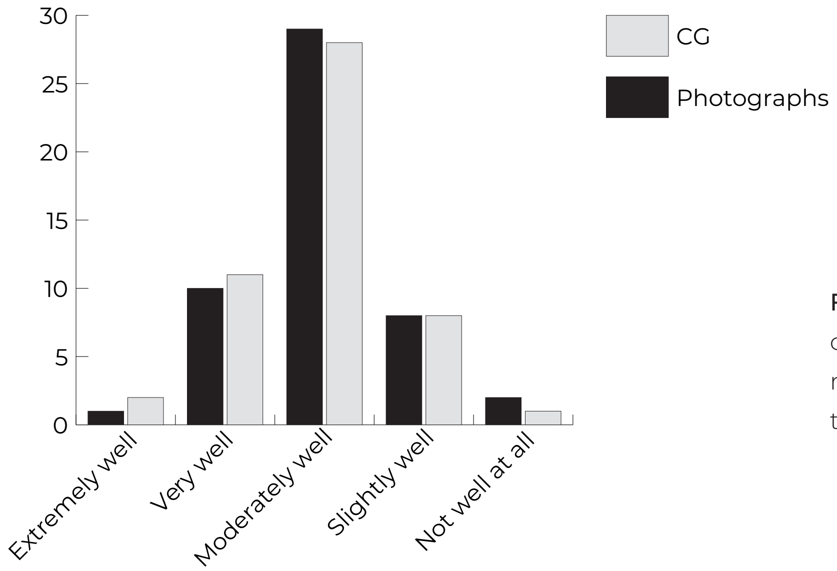

Figure 17: The distribution of participants expression recognition skills., between the two groups.

Afterwards the participants were asked to rate the difficulty of determining the displayed expressions in the questionnaire. The participants could rate the difficulty on a Likert scale from extremely difficult to moderately easy. The groups showed no significant difference in questionnaire difficulty ($\chi 2(5, N=100) = 0.124$, $p = 0.910$, two-tailed). Figure 18 presents the distribution of the results.

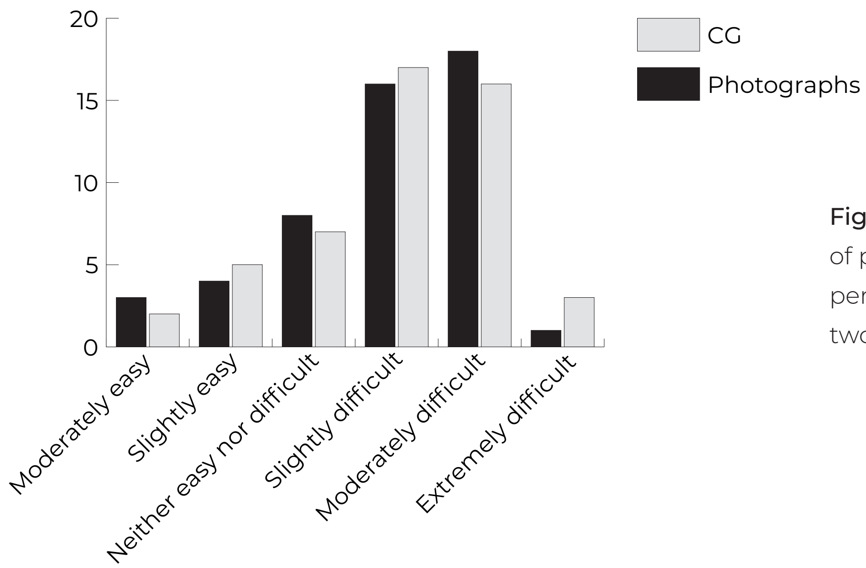

Figure 18: The distribution of participants difficulty perception, between the two groups.

4. FINDINGS

4.2 Recognition of the Intended Expressions

To verify if the recognition of the intended expressions was successful, the data has been processed into two different categories. The first subsection describes the results of the comparison of the individual expressions. The second subsection combines the expressions into families, decreasing the difficulty of assigning the right expression. This allows for a more general overview of the collected data.

4.2.1 Recognition of the Individual Expressions

To establish if the null hypothesis of the between-subjects experiment; *"There is no difference in the recognition of expressions between photographs and CG images"*, is significant, the individual questions were compared. Each expression has been displayed four times to a participant, twice per actor, in two different intensities.

The overall mean of recognition of expressions for the Group Photographs was M = 41.4% and for the Group CG M = 38,3% (t = 0.241; df = 76; p = 0.810, two-tailed). Figure 19 presents the percentage of correct results per expression for the Photograph Group.

Figure 20 presents the percentage of correct results per expression for the CG Group.

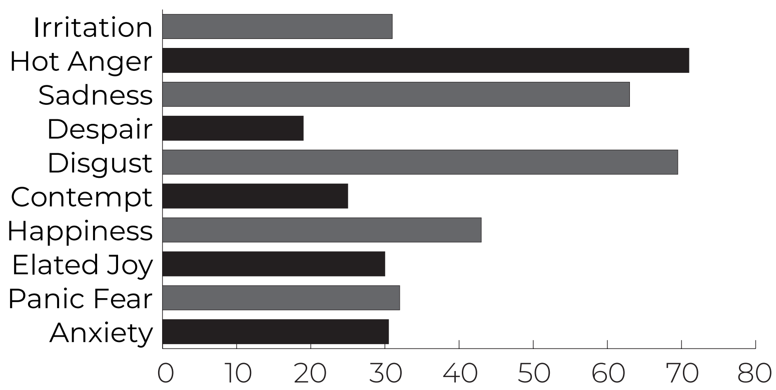

Figure 19: The percentage of correct expressions for the Photograph Group.

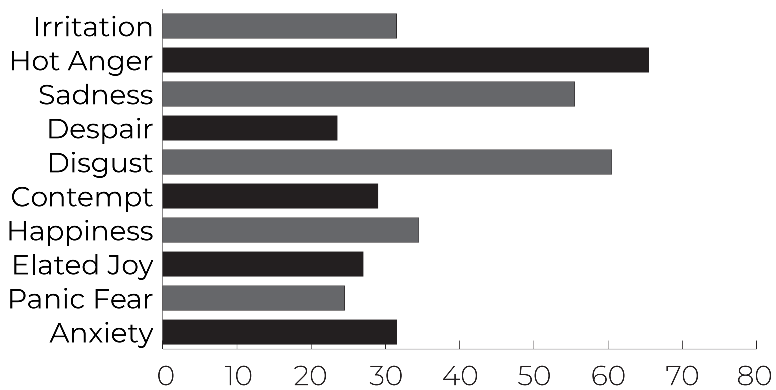

Figure 20: The percentage of correct expressions for the CG Group.

4. FINDINGS

4.2.2 Recognition of the Expression Families

Participants stated that the recognition of the expressions was difficult when they would miss the subtle differences within the short timeframe that the image was displayed. Hence the individual expressions have been combined within this section. The five families result in different conclusions, compared to data shown in 4.1.1. The overall score of recognition for Group Photographs was M = 60.1%, and for Group CG M = 56.2% (t = 0.691; df = 8; p = 0.509, two-tailed).

Combining the individual means from each intensity level within the Happiness and Elated Joy, Panic Fear and Anxiety, Despair and Sadness, Irritation and Hot Anger, and Disgust and Contempt families gave an overall result of M= 58%. Meaning that for both groups, slightly more than half of the participants recognized the intended expression family. Figure 21 presents the percentage of correct results per expression family for the Photograph Group. Figure 22 presents the percentage of correct results per expression family for the CG Group.

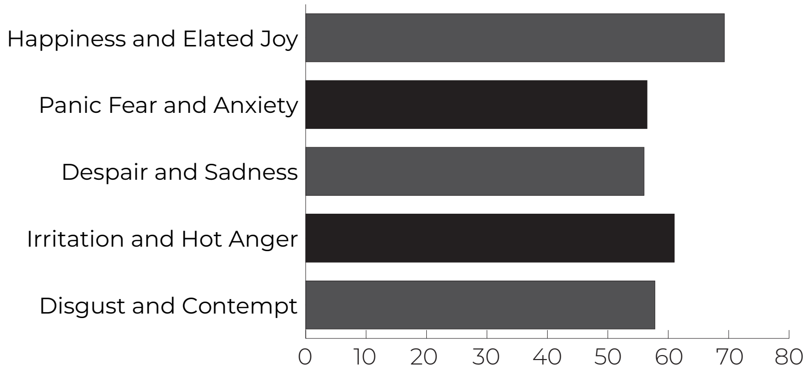

Figure 21: The percentage of correct results per expression family for the Photograph Group.

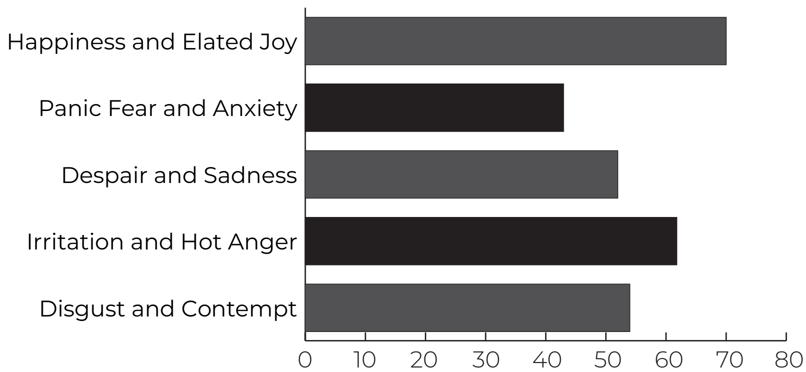

Figure 22: The percentage of correct results per expression family for the CG Group.

4. FINDINGS

4.3 Big Six versus the Secondary Expressions

The questionnaire included the Big Six expressions, these are the expressions that humans are able to recognize since birth (Prinz, 2004). Besides these six expressions, four more expressions were added, which are more difficult to recognize. This gave the study an extra layer of depth since it allowed for testing if both categories of expressions are recognizable in both groups. These secondary expressions can only be recognized when participants learned how to identify them in the past. The difference between Group Photographs and Group CG in the recognition of the Big Six expressions is M = 6.9% ($t = 1.139$; $df = 10$; $p = 0.281$, two-tailed). The difference in the recognition of Secondary Expressions is M = 9.2% ($t = -0.8$; $df = 6$; $p = 0.454$, two-tailed).

Noteworthy is the higher recognition of Group Photographs of the Big Six Expressions, and the higher recognition of the Secondary Expressions of Group CG. Nevertheless, in both groups, the Big Six Expressions have a higher mean score compared to the Secondary Expressions, which confirms the already established research.

In Appendix 4, Table 3 the split of the expressions into the Big Six and the Secondary Expressions is presented. The families as described at the beginning of this chapter do not apply to this section as the families consist of a blend between the Big Six and the Secondary Expressions. Figure 23 presents the percentage of correct results per expression for the Photograph Group. Figure 24 presents the percentage of correct results per expression for the CG Group.

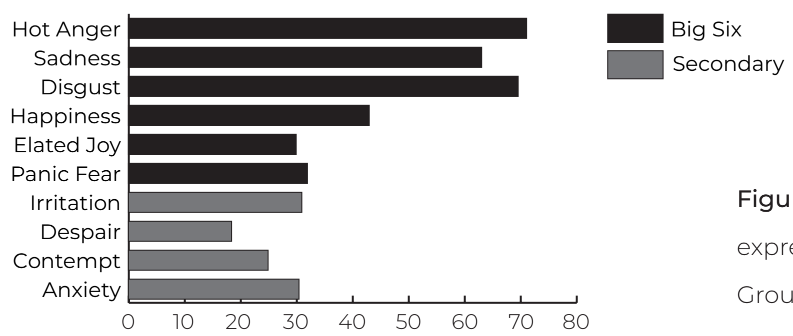

Figure 23: Correct results per expression for the Photograph Group.

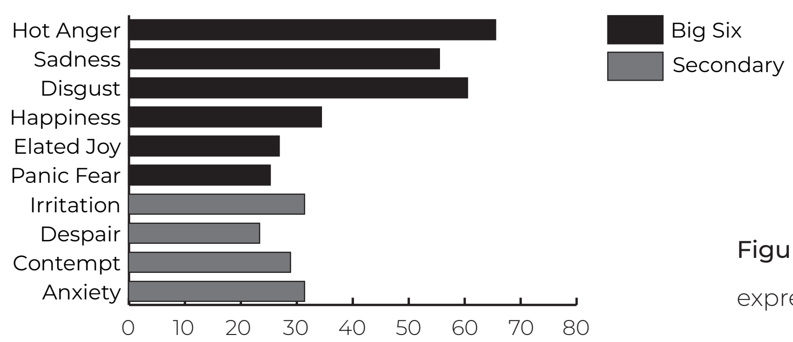

Figure 24: Correct results per expression for the CG Group.

4. FINDINGS

4.4 Actors Influence

This section looks into the influence of the male actor and the female actress. The section checks if there is a difference in the findings for either the still photographs or the CG images.

4.4.1 Actors Individual Expressions

The male actor had the following statistical results ($t = 0.139$; $df = 38$; $p = 0.890$, two-tailed). And the female actress had a statistical result of ($t = 0.317$; $df = 38$; $p = 0.753$, two-tailed). When combining the both groups, the male actor had a *M* = 29.6% and the female actress a *M* = 53%. Apendix 4, Table 5 displays all the questions divided into four categories; the male actor photographs and CG images, and the female actress photographs and CG images. Figure 25 displays the percentage correct recognition of each actor per expression for the Photographs Group. Figure 26 presents the percentage correct recognition of each actor per expression for the CG Group.

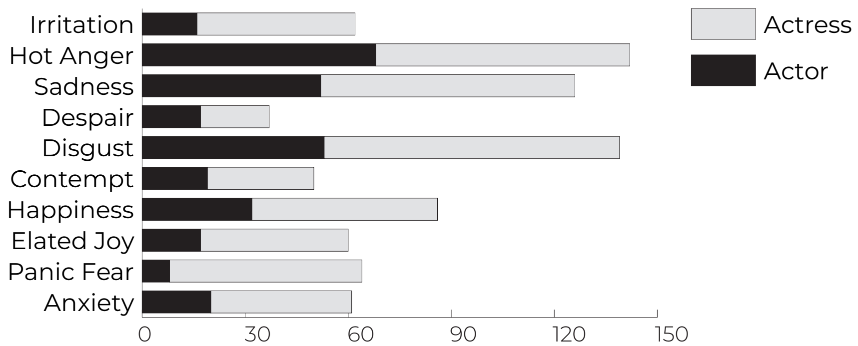

Figure 25: The percentage correct recognition of each actor per expression for the Photographs Group.

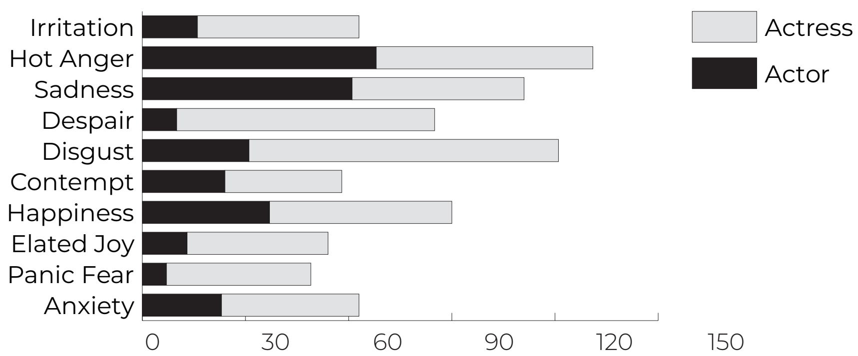

Figure 26: The percentage correct recognition of each actor per expression for the CG Group.

4. FINDINGS

4.4.2 Actors Family Expressions

The overall score of recognition for the male actor was *M* = 48.6% and for female actress *M* = 67.2%, a difference of 18.6% (t = -3.129; df = 8; p = 0.014, two-tailed). Appendix 4, Table 6 displays the same division as Appendix 4, Table 5, however, it combines the families as explained at the beginning of this chapter. Figure 27 presents the percentage correct recognition of each actor per expression family, for the Photographs Group. Figure 28 displays the percentage correct recognition of each actor per expression family, for the CG Group.

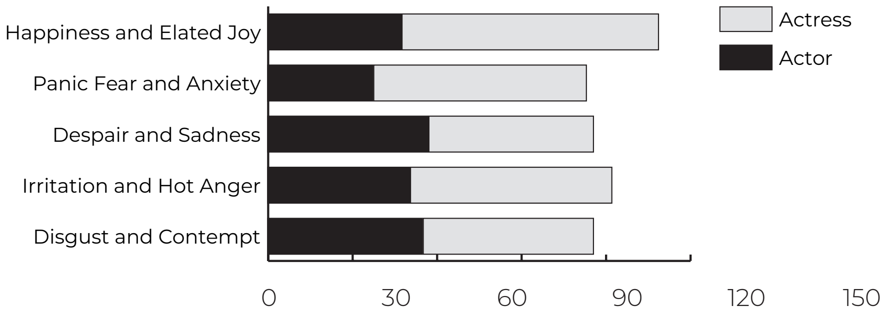

Figure 27: The percentage correct recognition of each actor per expression family, for the Photographs Group

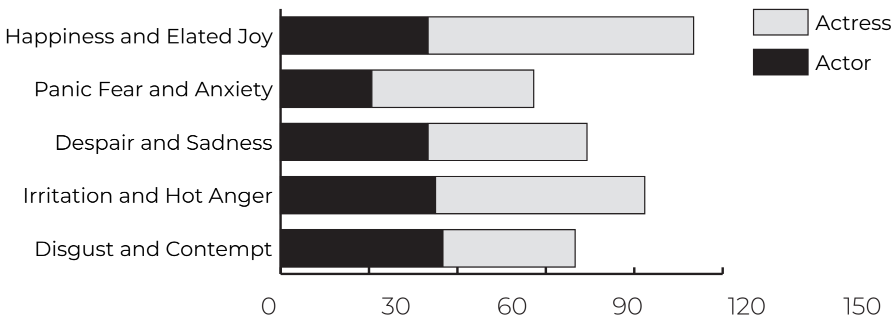

Figure 28: The percentage correct recognition of each actor per expression family, for the Photographs Group

4. FINDINGS

4.5 Intensity Levels

The expressions shown during the questionnaire contained, next to a male and a female version, two different intensity levels of the same expression. The MERT instrument also applied this technique to see if there was a difference in the recognition of expressions. Intensity level 1 expressions were more difficult to recognize since they are more subtle, and the intensity level 2 expressions were more defined and exaggerated compared to level 1.

4.5.1 Intensity Levels Individual Expressions

The Photograph Group resulted in a difference of recognition between the intenstiy levels of *M* = 13% (t = 1.467; df = 38; p = 1.51, two-tailed). See Figure 29 for the distribution.

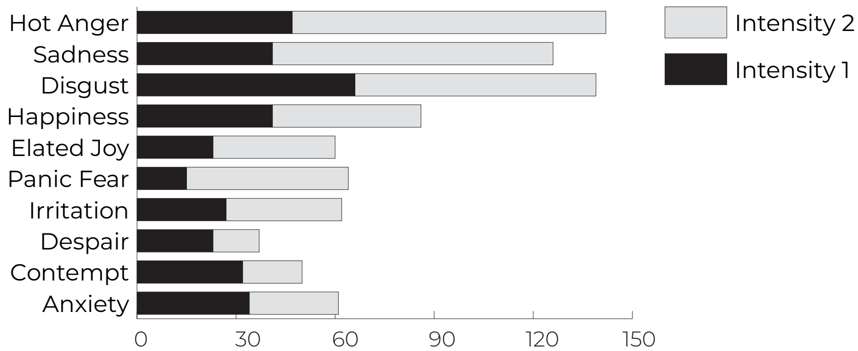

Figure 29: The distribution of correct answers of the Photograph group, between the two intensity levels.

The CG Group resulted in a difference of recognition between the intensity levels of *M* = 15% (t = 1.744; df = 38; p = 0.089, two-tailed). Figure 30 presents the distribution.

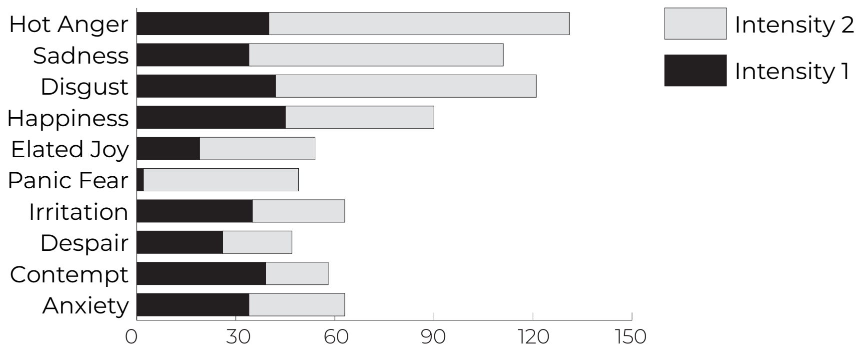

Figure 30: The distribution of correct answers of the CG group, between the two intensity levels.

4. FINDINGS

4.5.2 Intensity Levels Family Expressions

Comparing the results of the expression families, between the levels of intensity, of the Photographs Group, provided the results displayed in figure 31.

The level 1 intensity expressions of Group Photographs combined had a *M* = 54.7%, and the intensity 2 expressions a *M* = 65.5%. Which is a difference of *M* = 10.8% .

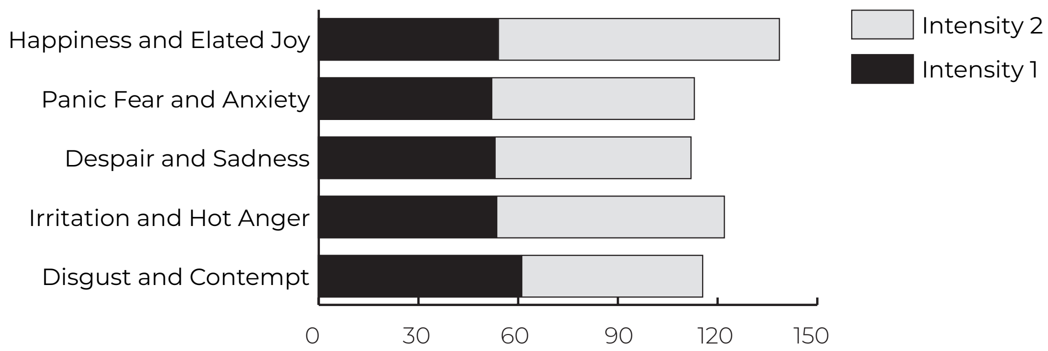

Figure 31: The results of the expression families, of the Photograph Group.

The level 1 intensity expressions of the CG Group combined had a *M* = 47%, and the intensity 2 expressions a *M* = 60.7%. A difference of *M* = 13.7%. The results are displayed in figure 32. Both groups presented a statistical result of (t = 0.655; df = 8; p = 0.531, two-tailed).

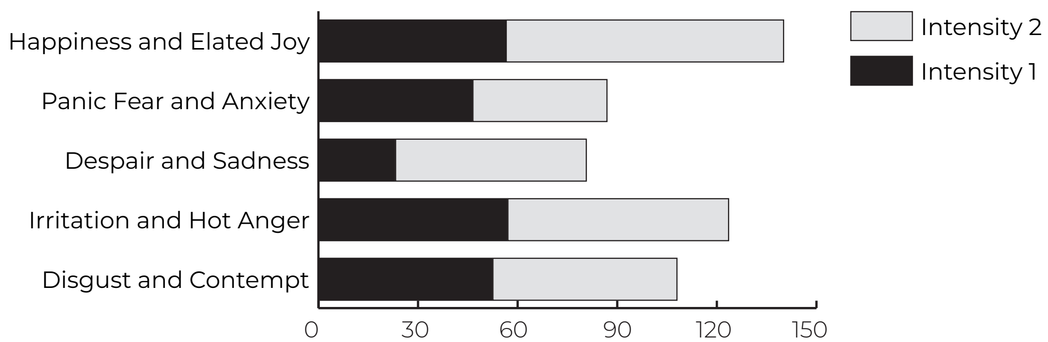

Figure 32: The results of the expression families, of the CG Group.

5. DISCUSSION

In the following chapter, the findings of the quantitative questionnaire are discussed similar to the separation of chapter 4. Both groups had an equal distribution of gender and age. The prior experience with CG avatars and expressions were equal for the groups. Neither played a moderate amount of video games or watch a moderate amount of movies containing VFX. Interestingly, even though the participants of both groups stated they are good at recognizing facial expressions, they felt the displayed expressions were difficult to determine. This could be a result of the short time that expressions where displayed, the Secondary Expressions, or the high intensity level. All of these possibilities are discussed in this chapter.

5.1 Recognition of Intended Expressions

5.1.1 Recognition of Individual Expressions

Even though both groups had a low score (41.1% versus 38.3%; $p = 0.810$) in recognizing the intended facial expression, the still photographs had a marginal higher correct result (3%) with no significant statistical difference. This low difference confirms that the feasibility of using the 3D CG models instead of photographs when the purpose is to convey expressions. A reason for the low overall scoring might be the short display time of the shown expressions. Since the study focused on the initial reaction of the participant, this might have been too short, although this was the same amount of the time used by the MERT-method (Bänziger et al., 2009).

Another reason could have been the length of the questionnaire. Even though the MERT-method showed 60 expressions per participant, this study used 40. Participants gave feedback they perceived the questionnaire to be repetitive, and it was difficult to keep their attention throughout the entire experiment. This statement gets confirmed in Qualtrics, where 100 participants completed the questionnaire, yet more than 240 possible participants started the questionnaire, meaning that 140 did not complete it.

5. DISCUSSION

5.1.2 Recognition of Expression Families

When reviewing the data of the Expression Families, the level of recognition increased to higher levels (60.1% versus 56.2%; $p = 0.509$). The results showed a small difference towards group A (4%), however this difference does not show any statistical difference, hence it does not prove if any of the groups were better.

A reason for this increase of correct chosen expressions is due to the combination of the expression sets with the most resemblance. The results showed that the participants are often better at recognizing the right family. The ability to recognize the right family instead of the right expression might occur due to the given limited time, which could be tested as an independent variable in future research. Another possibility is the static property of the displayed content. For example, recognizing the difference in happiness and elated joy might be easier when the expression is animated, in combination with audio. When shown in a static format the subtle difference might be lost.

Comparing the results to the findings from other research, Matsumoto and Hwang found an accuracy rate of 48% and 35% and Qu et al., an accuracy rate of 57,8%, the findings of this study score comparable accuracy results (Matsumo & Hwang, 2011; Qu et al., 2017).

A new hypothesis that comes to mind is; the recognition may be improved if the displayed content is more dynamic, for example, recognizing the difference in happiness and elated joy might be easier when the expression is animated, with or without in combination with audio. When shown in a static format the subtle differences might be lost.

5. DISCUSSION

5.2 Big Six versus Secondary Expressions

The difference in recognition of the Big Sex expressions between the groups was small (6.9%). The Secondary Expressions displayed a bigger gap (9.2%). What stands out when comparing the data, is that group A had a higher mean in the Big Six category, and group B scored higher in the Secondary Expressions. In order to get a better understanding, further research has to be conducted.

5.3 Actors Influence

5.3.1 Recognition of Individual Expressions by Different Actors

This section of the results showed a big difference between the correct recognized expressions. The male actor received almost half of the correct answers compared to the female actress (29% versus 53.5%; p = 0.890 & p = 0.753), for both groups. This outcome reflects prior research which shows that humans read facial expressions differently from male or females (Wingenbach et al., 2018; Cahill, 2006). Racial and ethnic characteristics, age, non-binary genders, and other personal factors, both of the actors and the viewers, may potentially also impact on the readability of expressions of an image. Further research using a more diverse group of actors and viewers may reveal further insights into this.
In terms of applicability this is extremely relevant to industry applications, and clearly needs to be further clarified. Guidelines should be created for CG developers to be able to accurately portray the correct expressivity for the 3D CG models.

5.3.2 Recognition of Expression Families by Different Actors

Similar to section 5.1.2, the data was converted for the Expression Families. The results are equal to the findings in 5.3; the male actor had a lower expression recognition score compared to the female actress; however, the difference is not as remarkable (48.6% versus 67.2%; p = 0.014). What stands out that, even with the expressions combined into families, the male actor did not score over 50% of correct recognized expressions. When analyzing the given feedback by the participants the male actor received some comments, which might support similar future studies. "...a bunch of the disgust, or maybe despair, expressions had the eyes looking down..." and "...the shown expressions seemed implausible since the actor did not look directly into the camera sometimes...". Research has shown that eye contact has a major role in the recognition of expressions and emotions. Smith et al. found that people often rely on different facial areas to understand individual facial expressions. Humans tend to look at the eyes for happiness, and to the mouth for fear (Smith et al., 2005). Another study found that the eyes supply the same amount of information as the whole face combined (Baron-Cohen et al., 1997).

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5.4 Intensity Levels

5.4.1 Recognition of Individual Expressions by Intensity Levels

As expected, group A had a higher score in recognizing the level 2 of intensities. The level 2 intensity expressions had a 13% higher correct score compared to the level 1 intensity expressions. Group B had similar results for both intensities, with a difference of 15% between level 1 and 2 intensity expressions. Comparing the photographs versus the CG images, both scored low for the recognition of level 1 intensity expressions, with a negligible difference of 3.3%. The level 2 intensity expressions showed similar results, a difference of 0.7% between both groups. However, both groups did not score above 50% in the recognition of intensity 2 expressions (48% versus 47%; $p = 0.151$ & $p = 0.089$). These results confirm that there is no difference in the recognition in either intensity level between the groups in this study.

5.4.2 Recognition of Expression Families by Intensity Levels

When adapting the data to the expression families, group A had an intensity level 1 result of 54.7% and group B 47%. For intensity level 2 group A had a result of 65.5% and group B 55.5% ($p = 0.531$). Compared to section 5.4.1 the difference between the groups is more noticeable. Group A scored better overall, which could mean that the subtle visual clues are lost when using CG images for the intensity 1 expressions.

5.5 Ethical Discussion

When established research, such as FACS and MERT, get portrayed on high realistic digital avatars, the ethical issues need to be considered into great detail. The possibilities of CG avatars are endless, for positive and negative use cases. Topics such as; beauty standards, the taking over of human jobs, porn limitations, and who owns the digital rights, need to be carefully explored in future research.

6. CONCLUSION AND KNOWLEDGE

In the final chapter, the contribution of knowledge and practical recommendations are listed. Followed by the established limitations and the possibilities for future research. This study was a between-subjects experiment that aimed to get insight into the differences and similarities of facial recognition of human expressions, in order to help the development of lifelike CG human faces, and found the following results. There were no noteworthy differences in the recognition of facial expressions between traditional photographs and computer graphic images. The photographs scored slightly better in almost every subcategory, however, the difference was insignificant. Nevertheless, both groups did not show high percentages of expression recognition, and most results had an average of approximately 50%.

6.1 Contribution of Knowledge

The main goal of this study was to establish if there was a difference in the recognition of facial expressions between still traditional photographs, and highly realistic computer graphic images. 100 Participants, divided over two groups, were tasked to select the intended expression of a series of images. Group A saw only traditional photographs, while group B saw computer-generated images. Afterwards the results were compared and presented. Even though the field of photogrammetry has been around for several decades, the ability to capture realistic humans is a rather young area. The findings help to understand how to enhance computer-generated humans, and how to overcome the Uncanny Valley effect. Since both groups scored the same level of recognition, the question arises of when to use each method.

Traditional photographs scored slightly higher for expresional readability in comparison with computer graphics, as well as being considerably cheaper and easier to produce. This makes them perfect for media applications such as marketing and film, which rely on short deadlines and reduced financial budgets.

When a technology is chosen purely for its efficacy at conveying facial expressions, photographs seem to be equally impactful as 3D CG models, and because they are cheaper to produce there seems not reason to use 3D CG models.
This does not take into account that 3D CG models have benefits beyond static facial expressions captured from a single angle. Where a photograph captures only one perspective, a 3D CG model allows editing and changes potentially decades after the scene was captured. The 3D CG models can also be used in context that may require

6. CONCLUSION

dynamic animations, such as in-game animations, speech synthesis, and medical applications. Given that the results show that there is a comparable ability to recognize expressions between highly detailed models and the default medium, photographs, the use of 3D CG models is extremely relevant for both academic and industry research in the context where editability, animation, and post-capture control of the scene is important.

In addition to our main finding, there are two very relevant findings that may directly contribute to the quality of the development of 3D CG models. First, it seems people have more difficulty in correctly recognizing expressions of male humans, this seems to be backed up by other research (Wingenbach et al., 2018; Cahill, 2006). Hence, clear guidelines on this effect and how to attenuate it might be relevant for CG developers. Second, it seems eye contact is extremely important for the ability to recognize expressions. Therefore this research suggests that CG faces used in interactive media will be enhanced by the ability of the 3D CG model to maintain eye contact, or they might reduce the readability of their facial expressions. This is very important for user interfaces which are portraying avatars and focus on dialog based interactions.

6.2 Limitations

This study has potential limitations. First, the actors used for this study both had a western background. Research has shown that cultures and races show and read expressions differently across the world (Cheng, 2007). The same limitation is applicable to the participants, from which the largest section had a western background. For a more complete research, the study should take place with a wide cultural variety of actors and participants.

Another limitation might be the high level of involvement which has influence on this study (Ketelaar & Van Gisbergen, 2006; Ketelaar, Van Gisbergen & Beentjes, 2012). Participants were forced to make a decision of selecting an expression, while normally this is natural human behavior, instead of a questionnaire test. This type of forced choice does not mimic the natural situation when perceiving human expressions, which might cause the participants to overthink their choice. Finally, the last limitation was the low adaptance of the audience to computer graphics. Both groups had no affinity with video games or VFX movies, which might have caused the lower recognition rate of the computer graphic images.

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6.3 Further Research

This study acts as preparation for the VIBE project, and is only one of the first steps in exploring the possibilities of modern photogrammetry for the creation of highly realistic digital avatars. The data set allows for numerous other research options to add to the findings of this study. A wider set of actors, with different cultural backgrounds, ages, and genders, might present different results. For example, Cheng discusses ethnic and racial differences in expression perception, which could also add a new layer of depth to the study in this paper (Cheng, 2007).

Another interesting angle would be the addition of animation. Is there a difference in the recognition of facial expressions between traditional film and animated computer graphics? Delving into this topic would take more time because it requires the photogrammetry technique to capture and render individual frames, which scales up the production time of the questionnaire, unfortunately this was not possible in the given time for this thesis. Assuming that the addition of animation may enhance the recognition of intensity level 1 expressions.

Similarly, this study gave the participants a limited time window of two seconds to register the expression, because the study only focuses on the initial gut feeling of the participant. A follow-up study that scales up the time limit might find other interesting results (Bänziger et al., 2009). Alternative methods for registering expression recognition by viewers may be possible, such as biometric monitoring of the viewers while they are looking at the CG or photographed faces.

During the study, only unaltered photogrammetry data was used, which resulted in raw and uncleaned three-dimensional models. If a game developer enhances the shaders of the model and develops realistic skin, hair, and eyes, the results might differ. Of course, this is time-consuming and very specialized work which requires time, financial budget, and specialized character artist skills. Testing could evaluate whether these adjustments improve the expression readability, or whether these changes evoke the UV problem.

The researcher his preference for future research is to examine how to attenuate the differences between the readability of facial expressions of male versus female faces, which may be beneficial for multiple aspects of the work performed by 3D character artists and CG developers; however, this study has shown that there are many areas of this field that currently remain unexplored and that may have significant impact on future applications of digital human technologies.

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8. APPENDIX

Appendix 1

Table 1:

Abbreviations used for each expression in the data.

Abbreviation	Expression
K	Irritation
H	Hot Anger
T	Sadness
Z	Despair
E	Disgust
V	Contempt
F	Happiness
U	Elated Joy
P	Panic Fear
A	Anxiety

Table 2

Overview of items, format and expression presented in the order of testing.

Test A

Order	Variable	Format	Target Value	Answer Expression	Intensity	Actor
1	SP1FM	SP	F	happiness	1	Male
2	SP2EF	SP	E	disgust	2	Female
3	SP2FF	SP	F	happiness	2	Female
4	SP2AM	SP	A	anxiety	2	Male
5	SP2UF	SP	U	elated joy	2	Female
6	SP2TF	SP	T	sadness	2	Female
7	SP1HM	SP	H	hot anger	1	Male
8	SP1TM	SP	T	sadness	1	Male
9	SP1AF	SP	A	anxiety	1	Female
10	SP1EF	SP	E	disgust	1	Female
11	SP1KM	SP	K	irritation	1	Male
12	SP1FF	SP	F	happiness	1	Female

Test A

Order	Variable	Format	Target Value	Answer Expression	Intensity	Actor
13	SP2PF	SP	P	panic fear	2	Female
14	SP1VM	SP	V	contempt	1	Male
15	SP2ZM	SP	Z	despair	2	Male
16	SP1PM	SP	P	panic fear	1	Male
17	SP1VF	SP	V	contempt	1	Female
18	SP2EM	SP	E	disgust	2	Male
19	SP1ZF	SP	Z	despair	1	Female
20	SP2VF	SP	V	contempt	2	Female
21	SP1AM	SP	A	anxiety	1	Male
22	SP2HM	SP	H	hot anger	2	Male
23	SP1KF	SP	K	irritation	1	Female
24	SP2PM	SP	P	panic fear	2	Male
25	SP2AF	SP	A	anxiety	2	Female
26	SP2VM	SP	V	contempt	2	Male
27	SP1HF	SP	H	hot anger	1	Female
28	SP2TM	SP	T	sadness	2	Male
29	SP2UM	SP	U	elated joy	2	Male
30	SP2ZF	SP	Z	despair	2	Female
31	SP2KM	SP	K	irritation	2	Male
32	SP1ZM	SP	Z	despair	1	Male
33	SP2HF	SP	H	hot anger	2	Female
34	SP2KF	SP	K	irritation	2	Female
35	SP1EM	SP	E	disgust	1	Male
36	SP1PF	SP	P	panic fear	1	Female
37	SP2FM	SP	F	happiness	2	Male
38	SP1UF	SP	U	elated joy	1	Female
39	SP1TF	SP	T	sadness	1	Female
40	SP1UM	SP	U	elated joy	1	Male

Test B

Order	Variable	Format	Target Value	Answer Expression	Intensity	Actor
41	CG1FM	CG	F	happiness	1	Male
42	CG2EF	CG	E	disgust	2	Female
43	CG2FF	CG	F	happiness	2	Female
44	CG2AM	CG	A	anxiety	2	Male
45	CG2UF	CG	U	elated joy	2	Female
46	CG2TF	CG	T	sadness	2	Female
47	CG1HM	CG	H	hot anger	1	Male
48	CG1TM	CG	T	sadness	1	Male
49	CG1AF	CG	A	anxiety	1	Female
50	CG1EF	CG	E	disgust	1	Female
51	CG1KM	CG	K	irritation	1	Male
52	CG1FF	CG	F	happiness	1	Female
53	CG2PF	CG	P	panic fear	2	Female
54	CG1VM	CG	V	contempt	1	Male
55	CG2ZM	CG	Z	despair	2	Male
56	CG1PM	CG	P	panic fear	1	Male
57	CG1VF	CG	V	contempt	1	Female
58	CG2EM	CG	E	disgust	2	Male
59	CG1ZF	CG	Z	despair	1	Female
60	CG2VF	CG	V	contempt	2	Female
61	CG1AM	CG	A	anxiety	1	Male
62	CG2HM	CG	H	hot anger	2	Male
63	CG1KF	CG	K	irritation	1	Female
64	CG2PM	CG	P	panic fear	2	Male
65	CG2AF	CG	A	anxiety	2	Female
66	CG2VM	CG	V	contempt	2	Male
67	CG1HF	CG	H	hot anger	1	Female
68	CG2TM	CG	T	sadness	2	Male
69	CG2UM	CG	U	elated joy	2	Male
70	CG2ZF	CG	Z	despair	2	Female
71	CG2KM	CG	K	irritation	2	Male

Test B

Order	Variable	Format	Target Value	Answer Expression	Intensity	Actor
72	CG1ZM	CG	Z	despair	1	Male
73	CG2HF	CG	H	hot anger	2	Female
74	CG2KF	CG	K	irritation	2	Female
75	CG1EM	CG	E	disgust	1	Male
76	CG1PF	CG	P	panic fear	1	Female
77	CG2FM	CG	F	happiness	2	Male
78	CG1UF	CG	U	elated joy	1	Female
79	CG1TF	CG	T	sadness	1	Female
80	CG1UM	CG	U	elated joy	1	Male

Appendix 2

Informed Consent Form

Welcome to my masters research study!

We are interested in understanding emotional recognition in human faces. Please be assured that your responses will be kept completely confidential.

The study should take you around five minutes to complete.
Your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to contact the Principal Investigator in the study to discuss this research, please e-mail *relouw.j@buas.nl*.

By clicking the button below, you acknowledge that your participation in the study is voluntary, you are 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason.

Please note that this survey will be best displayed on a laptop or desktop computer.
Some features may be less compatible for use on a mobile device.

You will be tasked with recognizing human facial expressions;

1. You will be presented with short displayed photographs of humans.
2. Afterwards you will be tasked to select the intended expresions from ten possible options.
   The photos are randomized and the same expression can be presented twice.
3. When the photos questions are completed, some questions regarding your experience in recognition are asked.

Thank you for your help and time!

- ◯ I consent, begin the study
- ◯ I do not consent, I do not wish to participate

Appendix 3

Photogrammetry Consent Form

Breda University OF APPLIED SCIENCES

Photogrammetry rig release form

The undersigned enters into this agreement with Breda University of Applied Sciences represented by producer, _____________________________ ("Producer"). I have been informed and understand that the Producer is producing a series of photographs and a subsequent static and/or animated digital 3D model of me ("Product") and that through this activity my likeness, image, appearance and expressions are being recorded and made a part of that production for research and education by Breda University of Applied Sciences.

1. I grant the Producer and its designees the right to use my likeness, image, appearance, and expressions as embodied in the Product whether recorded on or transferred to photographs or other media, now known or later developed. This grant includes without limitation the right to edit, mix or duplicate and to use or re-use the Product in whole or part as the Producer may elect. The Producer or its designee shall have complete ownership of the Product in which I appear, including copyright interests, and I acknowledge that I have no interest or ownership in the Product or its copyright.

2. I also grant the Producer and its designees the right to broadcast, exhibit, market, present, and otherwise distribute the Product, either in whole or in parts, and either alone or with other products, for internal use, for educational purposes, closed-circuit exhibition, or any other purpose that the Producer or its designees in their sole discretion may determine. This grant includes the right to use the Product for promoting or publicizing any of the uses.

3. I confirm that I have the right to enter into this Agreement, that I am not restricted by any commitments to their parties. I hereby give all clearances and transfer to Breda University of Applied Sciences all copyright and otherwise, for use of my likeness, image, appearance and expressions embodied in the Product. I expressly release and indemnify the Producer and Breda University of applied Sciences and its officers, employees, agents from any and all claims known and unknown arising out of or in any way connected with the above granted uses and representations. The rights granted the Producer herein are perpetual and worldwide.

4. In consideration of all the above, I hereby acknowledge receipt of reasonable and fair consideration from the Producer.

I have read the foregoing and understand its terms and stipulations and agree to all of them:

Name ____

Telephone number ____

Signature ____

Date______________________

(If the person signing is under age 18, a parent or legal guardian must sign below.)

I hereby certify that I am the parent or legal guardian of the model named above and I give my consent without reservation to the foregoing on behalf of him or her.

Name of Parent or Guardian ___________________________

Signature of Parent or Guardian ___________________________

Date__________________

DISCOVER YOUR WORLD

Appendix 4

Table 1:

Part 1. All the data of the questionaire combined into one spreadsheet.

SP	Irritation	Hot Anger	Sadness	Despair	Disgust	Contempt	Happiness	Elated Joy	Panic Fear	Anxiety	Number of Participants	Correct %
INTESITY 1												
SP2EF	0	0	0	1	48	1	0	0	0	0	50	96%
SP2FF	0	0	0	0	0	0	14	36	0	0	50	28%
SP2AM	5	0	1	11	4	2	0	2	16	9	50	18%
SP2UF	1	0	0	1	0	0	11	25	8	4	50	50%
SP2TF	1	0	43	5	1	0	0	0	0	0	50	86%
SP2PF	0	1	0	1	1	0	0	1	43	3	50	86%
SP2ZM	3	0	0	7	5	7	0	0	8	20	50	14%
SP2EM	2	21	1	1	25	0	0	0	0	0	50	50%
SP2VF	23	1	0	1	2	16	3	1	0	3	50	32%
SP2HM	3	45	0	0	0	1	0	0	0	1	50	90%
SP2PM	1	0	5	8	13	4	0	0	6	13	50	12%
SP2AF	5	2	0	4	3	4	0	0	14	18	50	36%
SP2VM	17	14	0	1	15	2	0	0	0	1	50	4%
SP2TM	0	0	42	7	0	0	0	0	1	0	50	84%
SP2UM	0	0	0	2	0	3	33	12	0	0	50	24%
SP2ZF	0	0	7	7	10	1	0	0	18	7	50	14%
SP2KM	6	0	21	10	6	0	0	0	0	7	50	12%
SP2HF	0	50	0	0	0	0	0	0	0	0	50	100%
SP2KF	29	4	0	2	2	12	0	0	0	1	50	58%
SP2FM	3	0	0	0	0	8	31	7	0	1	50	62%
INTESITY 2												
SP1FM	9	0	7	6	2	11	1	2	0	12	50	2%
SP1HM	13	23	1	1	4	6	0	0	2	0	50	46%
SP1TM	8	0	10	11	5	16	0	0	0	0	50	20%
SP1AF	5	1	0	4	1	5	0	0	11	23	50	46%
SP1EF	2	5	0	3	38	1	1	0	0	0	50	76%
SP1KM	10	1	7	5	10	13	0	0	0	4	50	20%
SP1FF	1	0	0	0	0	0	40	9	0	0	50	80%
SP1VM	7	3	2	4	17	17	0	0	0	0	50	34%
SP1PM	5	0	11	12	2	3	0	0	2	15	50	4%
SP1VF	20	2	1	4	0	15	5	2	1	0	50	30%
SP1ZF	0	0	5	13	0	0	0	0	9	23	50	26%
SP1AM	7	0	3	12	8	6	0	0	3	11	50	22%
SP1KF	17	1	2	6	1	13	1	0	0	9	50	34%
SP1HF	18	24	0	1	1	5	0	0	1	0	50	48%
SP1ZM	3	1	20	10	3	3	0	0	0	10	50	20%
SP1EM	10	0	2	3	28	6	0	0	0	1	50	56%
SP1PF	2	0	0	2	0	6	1	0	13	26	50	26%
SP1UF	0	0	0	0	0	3	29	18	0	0	50	36%
SP1TF	4	0	31	6	0	4	0	1	0	4	50	62%
SP1UM	5	0	6	6	2	16	4	5	0	6	50	10%
Number of Participants	**245**	**199**	**126**	**177**	**209**	**77**	**96**	**89**	**114**	**94**		
%	61%	50%	32%	44%	52%	19%	24%	22%	29%	24%		

Table 1:

Part 2. All the data of the questionaire combined into one spreadsheet.

CG	Irritation	Hot Anger	Sadness	Despair	Disgust	Contempt	Happiness	Elated Joy	Panic Fear	Anxiety	Number of Participants	Correct %
INTESITY 1												
CG2EF	0	0	0	0	48	1	0	0	0	1	50	96%
CG2FF	0	0	0	0	0	0	11	39	0	0	50	22%
CG2AM	3	0	0	13	5	8	0	0	10	11	50	22%
CG2UF	0	0	0	2	1	0	7	25	13	2	50	50%
CG2TF	1	0	31	6	4	4	0	0	2	2	50	62%
CG2PF	0	0	0	1	4	0	1	0	42	2	50	84%
CG2ZM	4	0	1	5	6	8	0	0	7	19	50	10%
CG2EM	4	15	0	0	31	0	0	0	0	0	50	62%
CG2VF	18	0	0	4	0	15	4	5	0	4	50	30%
CG2HM	5	45	0	0	0	0	0	0	0	0	50	90%
CG2PM	3	0	10	8	11	3	1	1	5	8	50	10%
CG2AF	7	5	1	3	2	2	1	0	11	18	50	36%
CG2VM	11	18	0	0	12	4	0	0	3	2	50	8%
CG2TM	1	1	46	1	1	0	0	0	0	0	50	92%
CG2UM	0	0	0	3	0	2	35	10	0	0	50	20%
CG2ZF	0	1	9	16	5	0	1	0	15	3	50	32%
CG2KM	3	1	25	8	7	3	0	0	1	2	50	6%
CG2HF	1	46	0	0	0	1	0	1	0	1	50	92%
CG2KF	25	7	1	5	1	8	1	0	0	2	50	50%
CG2FM	0	0	1	2	2	5	34	6	0	0	50	68%
INTESITY 2												
CG1FM	6	1	13	7	0	13	3	0	0	7	50	6%
CG1HM	14	23	0	1	0	6	0	0	2	4	50	46%
CG1TM	6	0	15	6	7	16	0	0	0	0	50	30%
CG1AF	9	0	1	3	0	2	0	0	13	22	50	44%
CG1EF	1	3	0	0	42	1	0	0	1	2	50	84%
CG1KM	13	1	3	2	7	19	0	0	0	5	50	26%
CG1FF	0	0	0	0	0	0	42	8	0	0	50	84%
CG1VM	5	1	1	3	20	20	0	0	0	0	50	40%
CG1PM	5	0	10	6	5	10	0	0	2	12	50	4%
CG1VF	18	0	1	4	0	19	0	2	0	6	50	38%
CG1ZF	1	0	2	21	1	4	0	0	10	11	50	42%
CG1AM	6	0	3	4	11	11	1	0	2	12	50	24%
CG1KF	22	3	4	5	3	7	0	1	1	4	50	44%
CG1HF	21	17	0	1	1	7	0	0	1	2	50	34%
CG1ZM	2	0	21	5	2	6	0	0	1	13	50	10%
CG1EM	7	1	1	3	0	3	0	1	11	23	50	0%
CG1PF	5	1	1	5	23	13	0	0	0	2	50	0%
CG1UF	0	0	0	1	0	0	32	16	1	0	50	32%
CG1TF	7	0	19	4	1	7	0	1	1	10	50	38%
CG1UM	4	0	5	6	2	19	9	3	0	2	50	6%
Number of Participants	**238**	**190**	**130**	**164**	**217**	**83**	**105**	**90**	**109**	**79**		
%	60%	48%	33%	41%	54%	21%	26%	23%	27%	20%		

Table 2:

Percentage of all the results from each group, and their differences.

STILL PHOTOGRAPHS	COMPUTER GRAPHIC IMAGES	
Correct Intended Expression	Correct Intended Expression	**Difference %**
2%	6%	4%
96%	96%	0%
28%	22%	6%
18%	22%	4%
50%	50%	0%
86%	62%	24%
46%	46%	0%
20%	30%	10%
46%	44%	2%
76%	84%	8%
20%	26%	6%
80%	84%	4%
86%	84%	2%
34%	40%	6%
14%	10%	4%
4%	4%	0%
30%	38%	8%
50%	62%	12%
26%	42%	16%
32%	30%	2%
22%	24%	2%
90%	90%	0%
34%	44%	10%
12%	10%	2%
36%	36%	0%
4%	8%	4%
48%	34%	14%
84%	92%	8%
24%	20%	4%
14%	32%	8%
12%	6%	6%
20%	10%	10%
100%	92%	8%
58%	50%	8%
56%	6%	56%
26%	0%	26%
62%	68%	6%
36%	32%	4%
62%	38%	24%
10%	6%	4%

Table 3:

Part 1. All the data of the questionaire altered for the expression families.

STILL PHOTOGRAPHS												
Happiness & Elated Joy	Irritation	Hot Anger	Sadness	Despair	Disgust	Contempt	Happiness	Elated Joy	Panic Fear	Anxiety	**Number of Participants**	Correct %
INTENSITY 1												
SP2FF	0	0	0	0	0	0	50		0	0	50	100%
SP2UF	1	0	0	1	0	0		36	8	4	50	72%
SP2UM	0	0	0	2	0	3		45	0	0	50	90%
SP2FM	3	0	0	0	0	8	38		0	1	50	76%
INTENSITY 2												
SP1UF	0	0	0	0	0	3		47	0	0	50	94%
SP1UM	5	0	6	6	2	16		9	0	6	50	18%
SP1FM	9	0	7	6	2	11	3		0	12	50	6%
SP1FF	1	0	0	0	0	0	49		0	0	50	98%
Panic Fear & Anxiety												
INTENSITY 1												
SP2AF	5	2	0	4	3	4	0	0		32	50	64%
SP2PF	0	1	0	1	1	0	0	1	46		50	92%
SP2PM	1	0	5	8	13	4	0	0	19		50	38%
SP2AM	5	0	1	11	4	2	0	2		25	50	50%
INTENSITY 2												
SP1AF	5	1	0	4	1	5	0	0		34	50	68%
SP1AM	7	0	3	12	8	6	0	0		14	50	28%
SP1PM	5	0	11	12	2	3	0	0	17		50	34%
SP1PF	2	0	0	2	0	6	1	0	39		50	78%
Despair & Sadness												
INTENSITY 1												
SP2TF	1	0	48		1	0	0	0	0	0	50	96%
SP2ZM	3	0	0	7	5	7	0	0	8	20	50	14%
SP2TM	0	0	49		0	0	0	0	1	0	50	98%
SP2ZF	0	0		14	10	1	0	0	18	7	50	28%
INTENSITY 2												
SP1ZM	3	1		30	3	3	0	0	0	10	50	60%
SP1TF	4	0	37		0	4	0	1	0	4	50	74%
SP1TM	8	0	21		5	16	0	0	0	0	50	42%
SP1ZF	0	0		18	0	0	0	0	9	23	50	36%
Irritation & Hot Anger												
INTENSITY 1												
SP2KM	6	0	21	10	6	0	0	0	0	7	50	12%
SP2HF	0	50	0	0	0	0	0	0	0	0	50	100%
SP2KF	33		0	2	2	12	0	0	0	1	50	66%
SP2HM		48	0	0	0	1	0	0	0	1	50	96%
INTENSITY 2												
SP1HM		36	1	1	4	6	0	0	2	0	50	72%
SP1KM	11		7	5	10	13	0	0	0	4	50	22%
SP1KF	18		2	6	1	13	1	0	0	9	50	36%
SP1HF		42	0	1	1	5	0	0	1	0	50	84%
Digust & Contempt												
INTENSITY 1												
SP2EF	0	0	0	1	49		0	0	0	0	50	98%
SP2EM	2	21	1	1	25	0	0	0	0	0	50	50%
SP2VF	23	1	0	1		18	3	1	0	3	50	36%
SP2VM	17	14	0	1		17	0	0	0	1	50	34%
INTENSITY 2												
SP1EM	10	0	2	3	34		0	0	0	1	50	68%
SP1EF	2	5	0	3	39		1	0	0	0	50	78%
SP1VM	7	3	2	4		34	0	0	0	0	50	68%
SP1VF	20	2	1	4	0	15	5	2	1	0	50	30%

Table 3:

Part 2. All the data of the questionaire altered for the expression families.

COMPUTER GRAPHIC IMAGES												
Happiness & Elated Joy	Irritation	Hot Anger	Sadness	Despair	Disgust	Contempt	Happiness	Elated Joy	Panic Fear	Anxiety	**Number of Participants**	Correct %
INTENSITY 1												
CG2FF	0	0	0	0	0	0	50		0	0	50	100%
CG2UF	0	0	0	2	1	0		32	13	2	50	64%
CG2UM	0	0	0	3	0	2		45	0	0	50	90%
CG2FM	0	0	1	2	2	5	40		0	0	50	80%
INTENSITY 2												
CG1UF	0	0	0	1	0	0		48	1	0	50	96%
CG1UM	4	0	5	6	2	19		12	0	2	50	24%
CG1FM	6	1	13	7	0	13	3	0	0	7	50	6%
CG1FF	0	0	0	0	0	0	50		0	0	50	100%
Panic Fear & Anxiety												
INTENSITY 1												
CG2AF	7	5	1	3	2	2	1	0		29	50	58%
CG2PF	0	0	0	1	4	0	1	0	44		50	88%
CG2PM	3	0	10	8	11	3	1	1	13		50	26%
CG2AM	3	0	0	13	5	8	0	0		21	50	42%
INTENSITY 2												
CG1AF	9	0	1	3	0	2	0	0		35	50	70%
CG1AM	6	0	3	4	11	11	1	0		14	50	28%
CG1PM	5	0	10	6	5	10	0	0	14		50	28%
CG1PF	5	1	1	5	23	13	0	0	2	0	50	4%
Despair & Sadness												
INTENSITY 1												
CG2TF	1	0	37		4	4	0	0	2	2	50	74%
CG2ZM	4	0		6	6	8	0	0	7	19	50	12%
CG2TM	1	1	47		1	0	0	0	0	0	50	94%
CG2ZF	0	1		25	5	0	1	0	15	3	50	50%
INTENSITY 2												
CG1ZM	2	0		26	2	6	0	0	1	13	50	52%
CG1TF	7	0	23		1	7	0	1	1	10	50	46%
CG1TM	6	0	21		7	16	0	0	0	0	50	42%
CG1ZF	1	0		23	1	4	0	0	10	11	50	46%
Irritation & Hot Anger												
INTENSITY 1												
CG2KM	4		25	8	7	3	0	0	1	2	50	8%
CG2HF		47	0	0	0	1	0	1	0	1	50	94%
CG2KF	32		1	5	1	8	1	0	0	2	50	64%
CG2HM		50	0	0	0	0	0	0	0	0	50	100%
INTENSITY 2												
CG1HM		37	0	1	0	6	0	0	2	4	50	74%
CG1KM	14		3	2	7	19	0	0	0	5	50	28%
CG1KF	25		4	5	3	7	0	1	1	4	50	50%
CG1HF		38	0	1	1	7	0	0	1	2	50	76%
Digust & Contempt												
INTENSITY 1												
CG2EF	0	0	0	0	49		0	0	0	1	50	98%
CG2EM	4	15	0	0	31	0	0	0	0	0	50	62%
CG2VF	18	0	0	4	0	15	4	5	0	4	50	30%
CG2VM	11	18	0	0		16	0	0	3	2	50	32%
INTENSITY 2												
CG1EM	7	1	1	3	3	0	0	1	11	23	50	6%
CG1EF	1	3	0	0	43		0	0	1	2	50	86%
CG1VM	5	1	1	3		40	0	0	0	0	50	80%
CG1VF	18	0	1	4	0	19	0	2	0	6	50	38%

Table 4:

Percentage of all the expression family results from each group, and their differences.

STILL PHOTOGRAPHS		*M* = 59.8%	COMPUTER GRAPHIC IMAGES		*M*= 56,2%	Combined *M* = 58%
Happiness & Elated Joy	**Correct %**	Group *M* = 69%	**Happiness & Elated Joy**	**Correct %**	Group *M* = 70%	Group *M* = 70%
INTENSITY 1		*M* = 85%	**INTENSITY 1**		*M* = 84%	*M* = 84,5%
SP2FF	100%		CG2FF	100%		
SP2UF	72%		CG2UF	64%		
SP2UM	90%		CG2UM	90%		
SP2FM	76%		CG2FM	80%		
INTENSITY 2		*M* = 54%	**INTENSITY 2**		*M* = 57%	*M* = 55,5%
SP1UF	94%		CG1UF	96%		
SP1UM	18%		CG1UM	24%		
SP1FM	6%		CG1FM	6%		
SP1FF	98%		CG1FF	100%		
Panic Fear & Anxiety		Group *M* = 57%	**Panic Fear & Anxiety**		Group *M* = 43%	Group *M* = 50%
INTENSITY 1		*M* = 61%	**INTENSITY 1**		*M* = 54%	*M* = 57,5%
SP2AF	64%		CG2AF	58%		
SP2PF	92%		CG2PF	88%		
SP2PM	38%		CG2PM	26%		
SP2AM	50%		CG2AM	42%		
INTENSITY 2		*M* = 52%	**INTENSITY 2**		*M* = 33%	*M* = 42,5%
SP1AF	68%		CG1AF	70%		
SP1AM	28%		CG1AM	28%		
SP1PM	34%		CG1PM	28%		
SP1PF	78%		CG1PF	4%		
Despair & Sadness		Group *M* = 56%	**Despair & Sadness**		Group *M* = 52%	Group *M* = 54%
INTENSITY 1		*M* = 59%	**INTENSITY 1**		*M*= 58%	*M* = 58,5%
SP2TF	96%		CG2TF	74%		
SP2ZM	14%		CG2ZM	12%		
SP2TM	98%		CG2TM	94%		
SP2ZF	28%		CG2ZF	50%		
INTENSITY 2		*M* = 53%	**INTENSITY 2**		*M* = 47%	*M* = 50%
SP1ZM	60%		CG1ZM	52%		
SP1TF	74%		CG1TF	46%		
SP1TM	42%		CG1TM	42%		
SP1ZF	36%		CG1ZF	46%		
Irritation & Hot Anger		Group *M* = 61%	**Irritation & Hot Anger**		Group *M* = 62%	Group *M* = 61,5%
INTENSITY 1		*M* = 69%	**INTENSITY 1**		*M* = 67%	*M* = 68%
SP2KM	12%		CG2KM	8%		
SP2HF	100%		CG2HF	94%		
SP2KF	66%		CG2KF	64%		
SP2HM	96%		CG2HM	100%		
INTENSITY 2		*M* = 54%	**INTENSITY 2**		*M* = 57%	*M* = 55,5%
SP1HM	72%		CG1HM	74%		
SP1KM	22%		CG1KM	28%		
SP1KF	36%		CG1KF	50%		
SP1HF	84%		CG1HF	76%		
Digust & Contempt		Group *M* = 56%	**Digust & Contempt**		Group *M* = 54%	Group *M* = 55%
INTENSITY 1		*M* = 55%	**INTENSITY 1**		*M* = 56%	*M* = 55,5%
SP2EF	98%		CG2EF	98%		
SP2EM	50%		CG2EM	62%		
SP2VF	36%		CG2VF	30%		
SP2VM	34%		CG2VM	32%		
INTENSITY 2		*M* = 57%	**INTENSITY 2**		*M* = 53%	*M* = 55%
SP1EM	68%		CG1EM	6%		
SP1EF	78%		CG1EF	86%		
SP1VM	68%		CG1VM	80%		
SP1VF	30%		CG1VF	38%		

Table 5:

All the data of the questionaire altered for the actors.

SP MALE		CG MALE	Correct %	Total %
SP1FM	2%	CG1FM	6%	
SP2AM	18%	CG2AM	22%	
SP1HM	46%	CG1HM	46%	
SP1TM	20%	CG1TM	30%	
SP1KM	20%	CG1KM	26%	
SP1VM	34%	CG1VM	40%	
SP2ZM	14%	CG2ZM	10%	
SP1PM	4%	CG1PM	4%	
SP2EM	50%	CG2EM	62%	
SP1AM	22%	CG1AM	24%	
SP2HM	90%	CG2HM	90%	
SP2PM	12%	CG2PM	10%	
SP2VM	4%	CG2VM	8%	
SP2TM	84%	CG2TM	92%	
SP2UM	24%	CG2UM	20%	
SP2KM	12%	CG2KM	6%	
SP1ZM	20%	CG1ZM	10%	
SP1EM	56%	CG1EM	0%	
SP2FM	62%	CG2FM	68%	
SP1UM	10%	CG1UM	6%	
M=	30%	*M=*	29%	30%
SP FEMALE		**CG FEMALE**	**Correct %**	**Total %**
SP1FF	80%	CG1FF	84%	
SP2AF	36%	CG2AF	36%	
SP1HF	48%	CG1HF	34%	
SP1TF	62%	CG1TF	38%	
SP1KF	34%	CG1KF	44%	
SP1VF	30%	CG1VF	38%	
SP2ZF	14%	CG2ZF	32%	
SP1PF	26%	CG1PF	0%	
SP2EF	96%	CG2EF	96%	
SP1AF	46%	CG1AF	44%	
SP2HF	100%	CG2HF	92%	
SP2PF	86%	CG2PF	84%	
SP2VF	32%	CG2VF	30%	
SP2TF	86%	CG2TF	62%	
SP2UF	50%	CG2UF	50%	
SP2KF	58%	CG2KF	50%	
SP1ZF	26%	CG1ZF	42%	
SP1EF	76%	CG1EF	84%	
SP2FF	28%	CG2FF	22%	
SP1UF	36%	CG1UF	32%	
M=	53%	*M=*	50%	51%

Table 6:

All the data of the questionaire altered for the actors family expressions.

FEMALE		*M* = 69%	MALE		*M*= 47,4%
Happiness & Elated Joy	**Correct %**	Group *M* = 91%	**Happiness & Elated Joy**	**Correct %**	Group *M* = 49%
SP2FF	100%		SP2FM	76%	
SP2UF	72%		SP2UM	90%	
CG2FF	100%		CG2FM	80%	
CG2UF	64%		CG2UM	90%	
SP1FF	98%		SP1FM	6%	
SP1UF	94%		SP1UM	18%	
CG1FF	100%		CG1FM	6%	
CG1UF	96%		CG1UM	24%	
Panic Fear & Anxiety		Group *M* = *65* %	**Panic Fear & Anxiety**		Group *M* = 34%
SP2AF	64%		SP2AM	50%	
SP2PF	92%		CG2PM	26%	
CG2AF	58%		CG2AM	42%	
CG2PF	88%		SP2PM	38%	
SP1AF	68%		SP1AM	28%	
SP1PF	78%		SP1PM	34%	
CG1AF	70%		CG1AM	28%	
CG1PF	4%		CG1PM	28%	
Despair & Sadness		Group *M* = 56%	**Despair & Sadness**		Group *M* = 52%
SP2TF	96%		SP2TM	98%	
SP2ZF	28%		SP2ZM	14%	
CG2TF	74%		CG2TM	94%	
CG2ZF	50%		CG2ZM	12%	
SP1TF	74%		CG1TM	42%	
SP1ZF	36%		CG1ZM	52%	
CG1TF	46%		SP1TM	42%	
CG1ZF	46%		SP1ZM	60%	
Irritation & Hot Anger		Group *M* = 71%	**Irritation & Hot Anger**		Group *M* = 52%
SP2HF	100%		CG2HM	100%	
SP2KF	66%		CG2KM	8%	
CG2HF	94%		SP2HM	96%	
CG2KF	64%		SP2KM	12%	
SP1KF	36%		CG1KM	28%	
SP1HF	84%		CG1HM	74%	
CG1KF	50%		SP1KM	22%	
CG1HF	76%		SP1HM	72%	
Digust & Contempt		Group *M* = 62%	**Digust & Contempt**		Group *M* = 50%
SP2EF	98%		CG2EM	62%	
SP2VF	36%		CG2VM	32%	
CG2EF	98%		SP2EM	50%	
CG2VF	30%		SP2VM	34%	
SP1EF	78%		CG1EM	6%	
SP1VF	30%		CG1VM	80%	
CG1EF	86%		SP1EM	68%	
CG1VF	38%		SP1VM	68%	

Table 7:

All the data of the questionaire altered for the intensity levels.

SP	Correct %	CG	Correct %	Combined %
INTENSITY 1	*M* =48%	INTENSITY 1	*M* =47%	*M* =47,5%
SP2EF	96%	CG2EF	96%	
SP2FF	28%	CG2FF	22%	
SP2AM	18%	CG2AM	22%	
SP2UF	50%	CG2UF	50%	
SP2TF	86%	CG2TF	62%	
SP2PF	86%	CG2PF	84%	
SP2ZM	14%	CG2ZM	10%	
SP2EM	50%	CG2EM	62%	
SP2VF	32%	CG2VF	30%	
SP2HM	90%	CG2HM	90%	
SP2PM	12%	CG2PM	10%	
SP2AF	36%	CG2AF	36%	
SP2VM	4%	CG2VM	8%	
SP2TM	84%	CG2TM	92%	
SP2UM	24%	CG2UM	20%	
SP2ZF	14%	CG2ZF	32%	
SP2KM	12%	CG2KM	6%	
SP2HF	100%	CG2HF	92%	
SP2KF	58%	CG2KF	50%	
SP2FM	62%	CG2FM	68%	
INTENSITY 2	*M* =35%	INTENSITY 2	*M* =32%	*M* =33,5%
SP1FM	2%	CG1FM	6%	
SP1HM	46%	CG1HM	46%	
SP1TM	20%	CG1TM	30%	
SP1AF	46%	CG1AF	44%	
SP1EF	76%	CG1EF	84%	
SP1KM	20%	CG1KM	26%	
SP1FF	80%	CG1FF	84%	
SP1VM	34%	CG1VM	40%	
SP1PM	4%	CG1PM	4%	
SP1VF	30%	CG1VF	38%	
SP1ZF	26%	CG1ZF	42%	
SP1AM	22%	CG1AM	24%	
SP1KF	34%	CG1KF	44%	
SP1HF	48%	CG1HF	34%	
SP1ZM	20%	CG1ZM	10%	
SP1EM	56%	CG1EM	0%	
SP1PF	26%	CG1PF	0%	
SP1UF	36%	CG1UF	32%	
SP1TF	62%	CG1TF	38%	
SP1UM	10%	CG1UM	6%	

Table 8:

All the data of the questionaire altered for the intensity levels of the family expressions.

STILL PHOTOGRAPHS		COMPUTER GRAPHIC IMAGES		
Happiness & Elated Joy	**Correct %**	**Happiness & Elated Joy**	**Correct %**	**Combined %**
INTENSITY 1	*M* =85%	INTENSITY 1	*M* =84%	*M* =84,5%
SP2FF	100%	CG2FF	100%	
SP2UF	72%	CG2UF	64%	
SP2UM	90%	CG2UM	90%	
SP2FM	76%	CG2FM	80%	
INTENSITY 2	*M* =54%	INTENSITY 2	*M* =57%	*M* =55,5%
SP1UF	94%	CG1UF	96%	
SP1UM	18%	CG1UM	24%	
SP1FM	6%	CG1FM	6%	
SP1FF	98%	CG1FF	100%	
Panic Fear & Anxiety		**Panic Fear & Anxiety**		
INTENSITY 1	*M* =61%	INTENSITY 1	*M* =54%	*M* =57,5%
SP2AF	64%	CG2AF	58%	
SP2PF	92%	CG2PF	88%	
SP2PM	38%	CG2PM	26%	
SP2AM	50%	CG2AM	42%	
INTENSITY 2	*M* =52%	INTENSITY 2	*M* =33%	*M* =42,5%
SP1AF	68%	CG1AF	70%	
SP1AM	28%	CG1AM	28%	
SP1PM	34%	CG1PM	28%	
SP1PF	78%	CG1PF	4%	
Despair & Sadness		**Despair & Sadness**		
INTENSITY 1	*M* =59%	INTENSITY 1	*M* =58%	*M* =58,5%
SP2TF	96%	CG2TF	74%	
SP2ZM	14%	CG2ZM	12%	
SP2TM	98%	CG2TM	94%	
SP2ZF	28%	CG2ZF	50%	
INTENSITY 2	*M* =53%	INTENSITY 2	*M* =47%	*M* =50%
SP1ZM	60%	CG1ZM	52%	
SP1TF	74%	CG1TF	46%	
SP1TM	42%	CG1TM	42%	
SP1ZF	36%	CG1ZF	46%	
Irritation & Hot Anger		**Irritation & Hot Anger**		
INTENSITY 1	*M* =69%	INTENSITY 1	*M* =67%	*M* =68,5%
SP2KM	12%	CG2KM	8%	
SP2HF	100%	CG2HF	94%	
SP2KF	66%	CG2KF	64%	
SP2HM	96%	CG2HM	100%	
INTENSITY 2	*M* =54%	INTENSITY 2	*M* =57%	*M* =55,5%
SP1HM	72%	CG1HM	74%	
SP1KM	22%	CG1KM	28%	
SP1KF	36%	CG1KF	50%	
SP1HF	84%	CG1HF	76%	
Digust & Contempt		**Digust & Contempt**		

Table 9:

All the data of the questionaire altered for the Big Six and Secondary Expressions.

The Big Six	Correct %	Group *M*	SP *M*	CG	Correct %	Group *M*	CG *M*	SP & CG *M*	Big Six *M*
SP1FM	2%	Happiness *M*=		CG1FM	6%	Happiness *M*=			
SP1FF	80%	43%	51%	CG1FF	84%	45%	46%	44%	49%
SP2FF	28%			CG2FF	22%				
SP2FM	62%			CG2FM	68%				
SP1EM	56%	Disgust *M*=		CG1EM	0%	Disgust *M*=			
SP1EF	76%	70%		CG1EF	84%	61%		65%	
SP2EF	96%			CG2EF	96%				
SP2EM	50%			CG2EM	62%				
SP1HM	46%	Hot Anger *M*=		CG1HM	46%	Hot Anger *M*=			
SP2HM	90%	71%		CG2HM	90%	66%		68%	
SP2HF	100%			CG2HF	92%				
SP1HF	48%			CG1HF	34%				
SP2PM	12%	Panic Fear *M*=		CG2PM	10%	Panic Fear *M*=			
SP1PF	26%	32%		CG1PF	0%	25%		28%	
SP2PF	86%			CG2PF	84%				
SP1PM	4%			CG1PM	4%				
SP1TM	20%	Sadness *M*=		CG1TM	30%	Sadness *M*=			
SP2TF	86%	63%		CG2TF	62%	56%		59%	
SP2TM	84%			CG2TM	92%				
SP1TF	62%			CG1TF	38%				
SP1UM	10%	Elated Joy *M*=		CG1UM	6%	Elated Joy *M*=			
SP1UF	36%	30%		CG1UF	32%	27%		29%	
SP2UF	50%			CG2UF	50%				
SP2UM	24%			CG2UM	20%				
Secondary Expressions									**Secondary *M***
SP1KM	20%	Irritation *M*=		CG1KM	26%	Irritation *M*=			
SP1KF	34%	31%	26%	CG1KF	44%	32%	29%	31%	28%
SP2KM	12%			CG2KM	6%				
SP2KF	58%			CG2KF	50%				
SP2AM	18%	Anxiety *M*=		CG2AM	22%	Anxiety *M*=			
SP1AF	46%	31%		CG1AF	44%	32%		31%	
SP1AM	22%			CG1AM	24%				
SP2AF	36%			CG2AF	36%				
SP1VM	34%	Contempt *M*=		CG1VM	40%	Contempt *M*=			
SP1VF	30%	25%		CG1VF	38%	29%		27%	
SP2VF	32%			CG2VF	30%				
SP2VM	4%			CG2VM	8%				
SP1ZF	26%	Despair *M*=		CG1ZF	42%	Despair *M*=			
SP2ZM	14%	19%		CG2ZM	10%	24%		21%	
SP2ZF	14%			CG2ZF	32%				
SP1ZM	20%			CG1ZM	10%				

Appendix 5

1. Group Similarities

Gender: Crosstabulation and Chi-Square Test

Gender * Group Crosstabulation

		Group SP	Group GR	Total
Gender	Female	27	30	57
	Male	23	20	43
Total		50	50	100

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	,367[a]	1	,545

Age: ANOVA Test

ANOVA

Group

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.709	3	.236	.935	.427
Within Groups	24.291	96	.253		
Total	25.000	99			

Education: Chi-Square Test

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.537[a]	6	.604
Likelihood Ratio	4.958	6	.549
N of Valid Cases	100		

VFX movie frequency: Chi-Square Test

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.731[a]	4	.444
Likelihood Ratio	4.891	4	.299
Linear-by-Linear Association	.638	1	.424
N of Valid Cases	100		

Video games frequency: Chi-Square Test

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.940[a]	4	.568
Likelihood Ratio	2.998	4	.558
Linear-by-Linear Association	.005	1	.944
N of Valid Cases	100		

Recognition of expressions: Chi-Square Test

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.122[a]	4	.891
Likelihood Ratio	1.141	4	.888
N of Valid Cases	100		

Difficulty of questionnaire: Chi-Square Test

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.526[a]	5	.910
Likelihood Ratio	1.574	5	.904
N of Valid Cases	100		

2. Recognition

Recognition of expressions: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Correctness	Equal variances assumed	,077	,782	,241	76	,810	,01538	,06372	-,11152	,14229
	Equal variances not assumed			,241	76,000	,810	,01538	,06372	-,11152	,14229

Recognition of family expressions: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	1,809	,216	,691	8	,509	,03600	,05213	-,08422	,15622
	Equal variances not assumed			,691	6,151	,515	,03600	,05213	-,09081	,16281

3. Big Six versus the Secondary Expressions

Big Six expressions: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Corectness	Equal variances assumed	,001	,978	1,139	10	,281	,11514	,10105	,281	,11514	,10105
	Equal variances not assumed			1,136	8,677	,286	,11514	,10135	,286	,11514	,10135

Secondary Expressions: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	1,205	,314	-,800	6	,454	-,02750	,03437	-,11160	,05660
	Equal variances not assumed			-,800	5,184	,459	-,02750	,03437	-,11492	,05992

4. Actors Influence

Male actor: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	,084	,773	,139	38	,890	,01200	,08633	-,16277	,18677
	Equal variances not assumed			,139	37,687	,890	,01200	,08633	-,16282	,18682

Female Actress: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	,236	,630	,317	38	,753	,02600	,08193	-,13986	,19186
	Equal variances not assumed			,317	37,955	,753	,02600	,08193	-,13986	,19186

Actors Family: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	1,031	,340	-3,129	8	,014	-,21600	,06904	-,37520	-,05680
	Equal variances not assumed			-3,129	6,324	,019	-,21600	,06904	-,38285	-,04915

5. Intensity Levels

Photographs Group intensity: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	6,576	,014	1,467	38	,151	,12900	,08792	-,04898	,30698
	Equal variances not assumed			1,467	33,040	,152	,12900	,08792	-,04986	,30786

CG Group intensity: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	4,151	,049	1,744	38	,089	,15500	,08890	-,02497	,33497
	Equal variances not assumed			1,744	35,345	,090	,15500	,08890	-,02541	,33541

Family intensity: Independent Samples Test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		t-test for Equality of Means			t-test for Equality of Means	
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Corectness	Equal variances assumed	1,482	,258	,655	8	,531	,03400	,05192	-,08573	,15373
	Equal variances not assumed			,655	6,293	,536	,03400	,05192	-,09163	,15963