

WHAT IS THE ROLE OF EMOTIONS ON FOOTBALL FANS IN
AFFECTING ONLINE VIDEO VIRALITY? (CASE STUDY OF
SALFORD CITY FC).

PhD Thesis

Joseph Silveira Ofori Asamoah

University of Salford, Salford Business School

2020

Submitted in partial fulfilment of the degree of Doctor of Philosophy

ABSTRACT

Viral video marketing is an expensive process and there is limited scholarly research about what makes video content go viral. A few online communities such as football clubs are keen to explore video virality to engage their audiences. One such club is the Salford City Football Club (FC) who have sponsored this research. Consequently, this study aims to identify the **key factors that drive the virality of online video content.**

To answer the research questions the STEPPS model by Jonah Berger, the Social Sharing of Emotions Theory (SSET), the Social Identity Theory (SIT) and Theory of Planned Behaviour (TPB) were some of the dominant models and theories in understanding the constructs of online video virality. A predominant variable that the STEPPS and SSET highlighted is emotional response from the video viewer, and thus, was primarily used as the theoretical basis for this work.

The primary data in this thesis comprised 60 respondents, of which were 32 football fans and 28 non-football fans. The Facial expression recognition software (Noldus 6.0) was used in combination with an online self-reporting web questionnaire to understand the emotions associated with the propensity to share content. In conjunction with emotions the thesis also investigated the role of groups (i.e. football fans and non-football fans) by analysing their effect on sharing which depicted variations on how both sets of groups respond to viral video and non-viral video stimuli.

Subsequently, the following are the **original contributions to knowledge:**

- 1) The research made theoretical advancements by examining specific emotions, arousal intensity and fan group dynamic using facial expression analysis on viral video stimuli. **The results from the thesis indicate that certain emotions are intrinsically viral and have a higher intention to share.** The research indicated that **fan group dynamics** also have a direct role to play into the extent a video is shared and should be considered as an important variable. The research explored the **existence of triggers which are specific events of importance that highlight the exact phase a video is most likely to be shared.**

- 2) The research made a **methodological advancement** in virality studies by **developing a unique method for predicting online videos in real time using emotional viewing patterns**. Related studies in virality prediction uses statistical algorithms to predict virality, this research took a different approach using the emotionality elicited from viewers obtained from facial expression analysis data.
- 3) The research made **methodological advancements** in understanding which method is more concurrent for measuring users' emotions when watching a video stimulus by comparing facial expression analysis data with self-report. The thesis concludes facial expression analysis is a more robust approach for measuring emotions however not for subjective norms like the "intention to share".

ACKNOWLEDGEMENTS

First, I will like to acknowledge God all mighty, who has been the source of my strength, insight, wisdom and understanding to undertake the thesis (Proverbs 2:6).

I would also like to acknowledge the following people, without whom, this thesis would not have been possible. I dedicate this thesis to Dr. Aleksej Heinze, without whom I would not have been able to go this far. For your endless support, motivation, and encouragement, there are times we may have had a diverging opinion on how to shape this research, but your wise counsel has always been appreciated when you meticulously read, corrected this document and provided useful suggestions. I also want to thank Dr. Adam Galpin whose added insight into the field of psychology was invaluable. Thank you for always understanding, and always helping me with the extra classes, the analysis and insight into different psychological themes which were instrumental in the research. My great appreciation also goes to Dr. Sunil Suhavadev who stepped in to ensure that that thesis is completed, your insight is duly appreciated.

I wish to dedicate this to my whole family, thank you for the support during the process. First, my appreciation goes to my lovely wife Mrs. Antoinette Asamoah who always will nudge me on the progress of my thesis in addition to her fervent prayers. To my father Dr. Joseph Ofori Asamoah who has always been my biggest believer and the main reason I decided to opt to

pursue a PhD. To my mother Dr. Maria Do Ceu Da Conceicao Silveira, who countless times asks me when I will finish my PhD. I also want to thank Rev Ben Mensah and Pastor Bright Brobbey who have been supporting me in prayers throughout this journey.

TABLE OF CONTENTS

ABSTRACT	2
ACKWOLEDGEMENTS	3
TABLE OF CONTENTS.....	5
LIST OF ABBREVIATIONS	9
CHARTS/DIAGRAMS	10
TABLES.....	11
DEFINITION OF TERMS	11
DECLARATION	13
INTRODUCTION	14
1.0.1 WHAT IS VIRALITY?	15
1.0.1.1 CHOHAN VIRAL MARKETING MODEL	17
1.0.1.2 JONAH BERGER STEPPS MODEL	19
1.0.1.3 DUAL – TB VIRAL VIDEO MARKETING MODEL	23
1.0.2 MEASURING VIDEO VIRALITY	25
1.0.2.1 METRIC FORMULATION	26
1.0.2.2 VIDEO POPULARITY	29
1.1 THEORETICAL FRAMEWORK	32
1.2 SOCIAL IDENTITY THEORY	32
1.3 SOCIAL SHARING OF EMOTIONS THEORY	34
1.4 RESEARCH PROBLEM DEFINITION	35
1.5 AIM AND OBJECTIVES	36
1.5.1 RESEARCH QUESTIONS	38
1.5.2 APPROACH TO SOLVE THE GAPS IN LITEARTURE	39
1.6 THESIS STRUCTURE	41
2.0 LITERATURE REVIEW	42
2.1 WHAT ARE BASIC EMOTIONS?	43
2.2 FACIAL ACTION CODING SYSTEM (FACS)	44
2.3 WHAT ARE FACIAL EXPRESSIONS?	46

2.3.1 WHAT IS FACIAL EXPRESSION ANALYSIS?	47
2.3.2 NEGATING FACTORS IN FACIAL EXPRESSIONS	49
2.3.2.1 MICRO EXPRESSIONS AND SUPPRESSION	53
2.3.3 ROLE OF EMOTION IN DECISION MAKING	56
2.3.4 THE SCOPE OF MOOD	57
2.4 VIRAL VIDEO PHENOMENON	58
2.4.1 NEGATING FACTORS IN VIRALITY	60
2.4.2 PREDICTING VIRALITY	63
2.5 CONCEPTUAL FRAMEWORK.....	65
2.5.1 HYPOTHESIS.....	67
2.6 SUMMARY	70
3.0 METHODOLOGY.....	72
3.1 PHILOSOPHICAL PARADIGM	72
3.1.1 CRITICAL RESEARCH	73
3.1.2 INTEPRETIVISM.....	75
3.1.3 POSITIVISM.....	77
3.3.4 THE CHOICE OF APPROPRIATE PARADIGM	78
3.3.5 THE NATURE OF THE RESEARCH	81
3.4 RESEARCH APPROACH.....	82
3.4.1 QUALITATIVE APPROACH.....	83
3.4.2 QUANTITATIVE APPROACH.....	83
3.5 INDUCTIVE AND DEDUCTIVE APPROACHES	86
3.6 QUERY-BASED TECHNIQUES FOR MEASURING EMOTIONS.....	87
3.7 QUESTIONNAIRE TYPES	88
3.7.1 LIKERT ITEM SCALE	89
3.7.2 WEB – BASED QUESTIONNAIRE.....	90
3.8 FACEREADER / FACIAL EXPRESSION ANALYSIS	96
3.9 VALIDITY	97
3.9.1.1 RELIABILITY	100
3.9.1.1 VALIDITY AND RELIABILITY OF THE FACEREADER IN RELATION TO DATA	103
3.9.1.2 VALIDITY AND RELIABILITY OF THE FACEREADER IN RELATION TO FACS	104

3.10 EXPERIMENTAL DESIGN ADOPTED	106
3.11 SUMMARY OF PARTICIPANTS	111
3.12 MATERIALS USED	113
3.13 BREAKDOWN OF DEMOGRAPHIC DATA	116
3.14 INTERNAL CONSISTENCY OF THE THESIS	120
3.15 REPLICABILITY AND GENERALISABILITY OF THE THESIS.....	123
3.16.1 MIXED RECRUITMENT ARRANGEMENTS	124
3.16.2 MIXED ENVIRONMENTS	125
3.17 THESIS RESEARCH JOURNEY.....	126
3.18 ETHICAL CONSIDERATIONS OF THE THESIS	128
4.0 ANALYSIS (RESULTS).....	129
4.1 RESULTS 1a	129
4.1.1 RESULTS 1b	157
4.1.2 RESULTS 1c.....	168
4.2 RESULTS 2	172
4.3 RESULTS 3	175
5.0 DISCUSSION AND FINDINGS.....	177
5.1 DISCUSSION RELATED TO RESULTS 1	177
5.2 DISCUSSION RELATED TO RESULTS 2	182
5.3 DISCUSSION RELATED TO RESULTS 3	184
5.4 SUMMARY OF RESEARCH FINDINGS.....	185
6.0 CONCLUSION	188
6.1 SUMMARY OF THESIS STRENGTH AND WEAKNESSES	193
6.2 KEY CONTRIBUTIONS.....	197
6.2.1 SOCIAL SHARING OF EMOTIONS (THEORETICAL CONTRIBUTION)	198
6.2.2 SOCIAL IDENTITY THEORY (THEORETICAL CONTRIBUTION)	198
6.2.3 METHODOLOGICAL CONTRIBUTION.....	199
6.3 FUTURE RESEARCH	199
6.4 REFLECTIONS ON MY ROLE AS A RESEARCHER	200
REFERENCES.....	202
APPENDIX	222

APPENDIX A SHARE THROUGH RATE METRICS	222
APPENDIX B SIGNIFICANT RESULTS DATA (1a).....	228
APPENDIX C FACE READER ORIGINAL DATA.....	230

LIST OF ABBREVIATIONS

ANS	AUTONOMIC NERVOUS SYSTEM
EEG	ELECTROENCAPHALOGRAM
FACS	FACIAL ACTION CODING SYSTEM
FMRI	FUNCTIONAL MAGNETIC RESONANCE IMAGING
GSR	GALVANIC SKIN RESPONSE
JBT	JONAH BERGER THEORY
NM	NEUROMARKETING
TA	THINK ALOUD
ERTA	EMOTIONAL RETROSPECTIVE THINK ALOUD
OWB	OBJECTIVE WELL BEING
PR	PROPAGATION RATE
RTA	RETROSPECTIVE THINK ALOUD
SEO	SEARCH ENGINE OPTIMISATION
SNS	SOCIAL NETWOTKING WEBSITES
SSET	SOCIAL SHARING OF EMOTIONS THEORY
SIT	SOCIAL IDENTITY THEORY
SWB	SUBJECTIVE WELL BEING
STR	SHARE THROUGH RATE
TPB	THEORY OF PLANNED BEHAVIOUR
WOM	WORD OF MOUTH

CHARTS/DIAGRAMS

Figure 1: Viral Twitter Example.....	15
Figure 2: Structural virality	16
Figure 3: Viral Marketing.....	18
Figure 4: Great Shark viral video	20
Figure 5: Negative Blendtec blender	22
Figure 6: Dual – TB model	24
Figure 7: Memoryless	30
Figure 8: Popular	31
Figure 9: Quality	31
Figure 10: Basic Emotions	44
Figure 11: Conceptual Framework	67
Figure 12: Questionnaire Types	88
Figure 13: Facial expression example	96
Figure 14: Research invitation sample.....	112
Figure 15: Viral Video 1	114
Figure 16: Viral Video 2	114
Figure 17: Non - Viral 1	115
Figure 18: Non - Viral 2	115
Figure 19a: Independent Demo.....	116
Figure 19b: Combined Demo.....	117
Figure 20: Lab vs Remote	119
Figure 21: Lab vs Remote variation	120
Figure 22: Lab Calibrations	121
Figure 23: Charlie but my finger	182

TABLES

TABLE 1: Approach to solve the gaps in Literature	40
TABLE 2: Philosophical Paradigms	78
TABLE 3: Synopsis	84
TABLE 4: Justification table.....	91
TABLE 5: Experimental Designs.....	106
TABLE 6: Demographics.....	122
TABLE 7: Research Findings.....	186
TABLE 8: Thesis Strength and Weaknesses.....	194

DEFINITION OF TERMS

AROUSAL: *arousal usually refers to the excitatory state of neurons or the propensity of neurons to discharge when appropriately activated (Heilman, 1997).*

ENGAGEMENT: *The user must become captivated by the campaign in some way to gain interest in it and further keep that interest high enough to decide to spend their time on it (Oden and Larsson, 2011).*

EMOTION: *An emotion is a complex psychological state that involves three distinct components: a subjective experience, a physiological response, and a behavioural (Hockenbury and Hockenbury, 2007).*

EMOTIONAL CONTAGION: *involves the convergence of one's emotional state with the emotional states of those with whom one is observing or interacting (Guadagno et al.,2013).*

PROPAGATION RATE: *The degree to which people are willing to pass a video to another (Watts and Parreti,2007) also classified as the Share Through Rate (Asamoah ,2016).*

SOCIAL CONTAGION: *The phenomenon where actions are influenced by interpersonal contact, impacting the aggregate diffusion and spread of behaviours, new products, ideas or epidemics*

which was built on different explanations ranging from the constructs of social conformity, homophily and awareness diffusion (Susarla, Oh and Tan,2012).

SOCIAL IDENTITY: *literally means being at one with a certain group, being like others in a certain group and seeing things from a group's perspective, acting to fulfil the expectations of the role, co-ordinating and negotiating interaction with role partners, and manipulating the environment to control the resources for which the role has a responsibility (Stets and Burke, 2000).*

SOCIAL NEUROSCIENCE: *social neuroscience is used to refer to a range of neural, physiological and endocrine measures that are used to explain social behaviour (Scheepers and Derks,2016).*

SOCIAL VALIDATION: *Is the tendency for individuals to look to others to see what others are doing to determine if a behaviour is normative and appropriate (Guadagno et al, 2013).*

THINK ALOUD: *The Think-aloud protocols involve participants thinking aloud as they are performing a set of specified tasks. Users are asked to say whatever they are looking at, thinking, doing, and feeling as they go about their task. This enables observers to see first-hand the process of task completion (rather than only its final product) (Nielsen and Pernice, 2006).*

USER EXPERINCE: *The state of focusing on having a deep understanding of users, what they need, what they value, their abilities, and their limitations (Usability, 2014).*

VIDEO MARKETING: *It is incorporating video in campaigns to promote a brand, product or service*

VIRAL MARKETING: *is used to describes the phenomenon by which individuals mutually share and spread marketing messages or information, initially sent out deliberately by marketers to take advantage of Word of Mouth behaviours (Lans, Ralf, Eliashberg, and Wierenga, 2010).*

VIRTUAL COMMUNITIES: *are online social networks in which people with common interest, goals or practices interact to share information and knowledge and share in social interactions (Chiu, Hsu and Wang,2006).*

RETROSPECTIVE THINK ALOUD: *A technique used in usability, and eye tracking in particular, to gather qualitative information on the user intents and reasoning during a test. It's a form*

of think aloud protocol, performed after the user testing session activities, instead of during them (Nielsen and Pernice, 2006).

SHARE THROUGH RATE: A standard metric for used for evaluating how people are willing to pass one video to another (Asamoah,2016).

DECLARATION

Some parts of this study have been presented in a conference which is listed below:

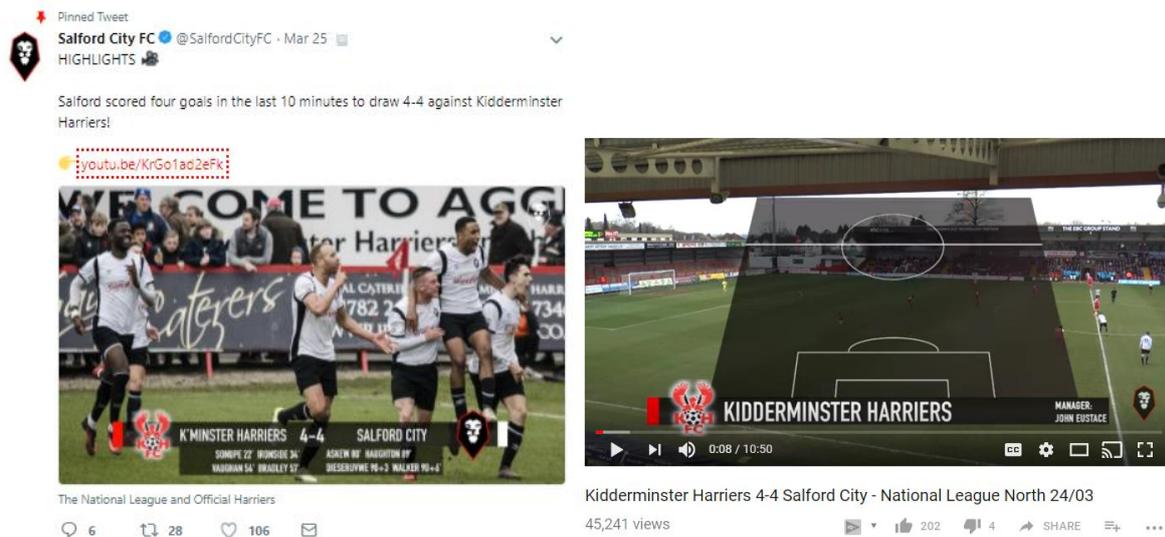
- Asamoah, J. (2016) “How to measure and predict video virality”: A statistical approach. UKAIS Conference in Information Systems, February 2016. (Presentation, Abstract and full paper accepted). Paper also submitted in the USIR Repository.
- Asamoah, J. (2018) “How emotions and social groups affect online videos in going viral”. Salford Postgraduate Annual Research Conference (SPARC), July 2018. Presentation.
- Asamoah, J. (2019) “Measuring user emotionality on online videos: A comparison between self-report and facial expression analysis”: A statistical approach. UKAIS Conference in Information Systems, April 2019.

INTRODUCTION

The growth of online video has seen an increase over the years, enhanced using online sharing platforms such as YouTube, which is expected to account for 69% of all consumer online traffic worldwide by 2017 (Cisco, 2015). With online videos rapidly becoming a means for users to satisfy their information and entertainment needs, businesses that fail to include it in their internet marketing strategies would lag as it is predicted to be a key part of the future of content marketing (Trimble, 2015). The potential reach of video is significant, YouTube, which is the online video hosting platform to be used in the current study receives more than 1 billion unique visitors each month (YouTube.com, 2016). This is just within 11 years of launching the platform in 2005. The high views can be attributed to producing different video content for various customer engagement touch points, linking it with different social media channels, and using targeted advertising (Clampa and Goeldi, 2013).

Botha (2014) indicates that the rise of video sharing giants like YouTube and Vimeo coupled with increased broadband and 4G connectivity has improved sharing functionality across social networking sites, thus, the role of the viral video has been adopted in many Integrated Marketing Communication (IMC) strategies. This is evident from the transfer of advertising budgets from TV advertising and search and direct response campaigns to viral video campaigns (Botha, 2014). Agrawal (2016) noted that online video platforms such as YouTube will have exceptional value for marketers looking to grow their audience and grow a pipeline of interested prospective customers. Getting YouTube views will become increasingly important and having a multi-channel marketing campaign will be critical for a business' success. Agrawal (2016) gave three main reasons why brands should be marketing on YouTube this include but is not limited to creating an image, building credibility and trust with clients and the fact that it is more engaging than other forms of media. It is in this regard brands and their advertising agencies are increasingly adding viral videos to their strategies.

Figure 1 Viral Twitter example



In the video pictures above Salford City Football Club (SCFC) managed to stage an incredible come back from 4-0 with 10 minutes to go to create a social media buzz which culminated with lots of shares and views. However, the reality is that not every video that is uploaded on YouTube and subsequently shared on a social media platform by Salford City FC gets any viral traction. In understanding what makes content viral, Howes (2012) argued that the mere fact a video is uploaded on YouTube and one perceives it to be great does not naturally covet the video status to become viral, as it is not just a natural occurrence, it can be intentionally engineered. In support of this assertion, virality researchers (e.g. Southgate, Westoby and Page, 2010 ; Berger and Milkman, 2012; Feroz Khan and Vong, 2014) noted that there are certain important variables that make videos such as the one above to go viral. What are the variables and most importantly what's virality?

1.0.1 WHAT IS VIRALITY?

Many social media marketers have defined virality in different contexts (Feroz Khan and Vong , 2014) referred to virality as videos that can be quickly shared and that become popular among social networks. Porter, Lance and Golan (2006) described virality as unpaid peer-to-peer communication of 'provocative' content originating from an identified sponsor using the Internet to persuade or influence an audience to pass along the content to others. Viral comes from the word "virus," which is a medical term used to describe a small infectious agent that can infect all types of organisms . Anyone who has published a hit post knows clicks and social

media impressions can seem to accelerate just as fast. This basic model of how viruses spread has informed how we understand the spread of digital content, but recent research on the subject complicates this understanding. Microsoft Research and Stanford University researchers recently applied the biological definition of virality to the spread of approximately one billion tweets and retweets on Twitter (Goel, Hofman and Watts, 2015). The researchers, led by Stanford University Assistant Professor Sharad Goel, came up with their definition of virality known as **structural virality**; where:

Figure 2 Structural Virality formula

$$v(T) = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n d_{ij}$$

Specifically, structural virality can be defined as the average distance between all pairs of nodes in a diffusion tree T ; that is, for $n > 1$ nodes, where d_{ij} denotes the length of the shortest path between nodes i and j . Equivalently, $v(T)$ is the average depth of nodes, averaged over all nodes in turn acting as a root. The metric provides a continuous measure of structural virality, with higher values indicating that adopters are, on average, farther apart in the cascade, and thus suggesting an intuitively viral diffusion event (Goel, Hofman and Watts, 2015). As with depth and average depth, over the set of all trees on n nodes is minimized on the star graph where $v(T)$. The desired definition of structural virality should not depend on these. In other words, regardless of what contagion process is responsible for some piece of content spreading or what network it is spreading over, the result is some pattern of adoptions that exhibits some structure.

Narrowing down the definition of virality can be very challenging as it can be specific to the structure of the platform that is applied (Peterson, 2014). An update to Facebook's insights - its page to help Facebook page owners track the performance analytics - introduced the option to see the "viral reach" of each post. When Facebook introduced it, the social media giant defined it as the number of people who created a story from a post on your Facebook page, divided by the number of "unique people" who have seen that original post. Hence, as it can be evidenced above that both platforms have a different outlook on virality.

YouTube on the other hand, defines virality in an entirely different pretext with many variables to be considered as there are several ways to gauge if a video has gone viral. **The underlying definitions suggest that video virality refers to just the rate at which videos are shared; however, it may also include more such as the number of views, the number of likes, subscriptions driven, or perhaps all the above.** The statistic perhaps most mentioned is number of views, and as sharing has become easier, the threshold requirement of sheer number of views has increased. YouTube personality Kevin Nalty (known as Nalts) recalls on his blog: "A few years ago, a video could be considered 'viral' if it hit a million views", but says as of 2011, only "if it gets more than 5 million views in a 3–7 day period" can it be considered "viral". To compare, 2004's "Numa Numa" received two million hits on Newgrounds in its first three months (a figure explained in a 2015 article as "a staggering number for the time").

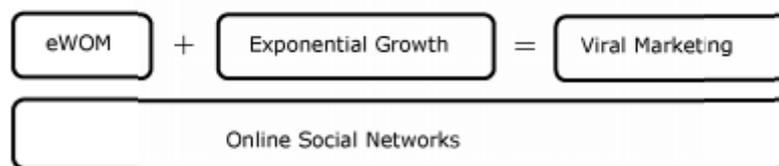
Nalts also posits three other considerations: buzz, parody, and longevity, which are more complex ways of judging a viral video's views. Buzz addresses the heart of the issue; the more a video is shared, the more discussion the video creates both online and offline. What he emphasizes is that the more buzz a video gets, the more views it gets. A study on viral videos by Carnegie Mellon University found that the popularity of the uploader affected whether a video would become viral, and having the video shared by a popular source such as a celebrity or a news channel also increases buzz. Buzz is also part of the algorithm YouTube uses to predict popular video parodies, spoofs and spin-offs which often indicate a popular video, with long-popular video view counts given with original video view counts as well as additional view counts given for the parodies. This in context brings up the notion of harnessing a video marketing model or models that empirically demonstrate how videos become viral.

1.0.1.1 CHOHAN VIRAL MARKETING MODEL

With consumers' increased resistance to traditional forms of advertising, marketers have turned to creative strategies to reach consumers, including viral marketing (Leskovec, Adamic and Huberman, 2007). Viral marketing can be defined as a form of peer-to-peer communication wherein people are encouraged to pass along promotional messages within their social networks (Bampo et al., 2008). Viral marketing also refers to strategies that allow an "easier, accelerated, and cost-reduced transmission of messages" by creating

environments for the exponential self-replication of marketing messages, increasing the “diffusion, spiritualization, and impact of the message” (Golan and Zaidner, 2008, p.3). Consumers are therefore motivated to spread these credible messages to their online community thus recruiting more customers (Phelps et al., 2004). The term “viral marketing” was first introduced in 1996 by Jeffrey Rayport (Kaplan and Haenlein, 2011), but while the term viral marketing has been around for some time, there is still disagreement about its definition (Camarero and San José, 2011; Phelps et al., 2004). The debate centers largely on whether viral marketing is simply another form of word-of-mouth (WOM) marketing or a complete and independent subset of marketing. The first writings in viral marketing in 1997 by Jurvetson and Draper (1997) defined viral marketing as “network-enhanced word-of-mouth”. Many authors followed their lead and have since referred to viral marketing as a form of eWOM (Berger and Milkman , 2012; Chen and Berger, 2013). Authors that equate viral marketing to eWOM argue that it forms part of an Integrated Marketing Communication(IMC) strategy and is based on the central components of WOM, i.e. the spread of a message from consumer to consumer via a social network such as Facebook or Twitter. Except that, instead of face-to-face communication, the medium through which the message spreads are digital media. Consequently, the term eWOM or electronic word-of-mouth was developed. On the other hand, not all authors agree that viral marketing is a form of WOM. Sohn , Gardner and Weaver (2013) would argue that if all requirements for a definition are not met, the concept of the definition cannot be used. Chohan (2013) defined viral marketing as a form of eWoM that has exponential growth, uses interactive multimedia and the message stays across the whole social network as depicted in the diagram below.

Figure 3 viral marketing



SOURCE: Chohan (2013)

Since this study places focus on videos, the definition of a viral marketing campaign has some slightly different components with emphasis on testing and dissemination. The Jonah Berger STEPPS model seen below is another model that tries to explain the dissemination of content.

1.0.1.2 JONAH BERGER STEPPS MODEL

There is still ongoing research into understanding what instigates virality by video marketing companies and academic institutions alike. An Australian production company recently added a new consideration to the viral debate, but proving, repeatedly, that they could, in fact, create viral content. The company, The Woolshed and Co., sought to better understand the elements of viral video content - and not just in academic sense, they also applied and utilised their learnings to create some very well-known viral videos. Their first attempt was to produce a short clip of a man jumping off a rock wall in Sydney only to be confronted by a shark. The video has so far racked up 38 million views. And it's easy to see why - it's well made, well executed, and it doesn't go too far - the guy doesn't suddenly end up in a physical battle with the shark that would take it totally beyond the realm of plausibility. The video also plays to the common emotional triggers of viral content - a recent study by [Fract.I.](#), for example, found that "Happiness", "Surprise" and "Admiration" are the three top emotional responses to viral images, all of which could also be applied to this video. **Such findings have also been supported by various other viral content studies where being able to generate a strong emotional response is obviously a great way to trigger subsequent audience action, something that this video does really well.** And interestingly, while many people debated the authenticity of the shark video, that debate only further fuelled its share count.

The project provided some great insights into the key elements of what goes viral the videos that Woolshed has created contains an element of surprise, something unexpected, which is one of the most common emotional triggers in highly shared content. In addition to that, each of the videos is relatively light-hearted, pointing to that second critical element in "Happiness" and each has a satisfaction element also, in that they come to a resolution, rather than leaving the audience hanging. But on top of this, Woolshed's videos also feel authentic. The creative team have obviously gone to a lot of effort to consider the real-world scenarios in which the characters find themselves in, and their attention to detail is great. If you go over the top, have the tornado carry the guy off into the clouds, for example, that would be unbelievable. But stay within the confines of plausible reality and people will more likely accept it.

Figure 4 Great Shark viral video



GoPro: Man Fights Off Great White Shark In Sydney Harbour

38,007,798 views

103K 27K SHARE SAVE ...

To further harness the understanding of virality, it is prudent to evaluate Jonah Berger's research. In his book, "contagious why things catch on", Berger (2013) analysed hundreds of contagious messages, products and ideas and hypothesised 6 main principles that can cause sharing. These can be postulated as follows:

- 1) **Social Currency:** How does it make people look to talk about a product.
- 2) **Public:** Can people see when others are using a product or engaging in desired behaviour. There is a need to design products and initiatives that design themselves and creates a behavioural residue that sticks around even after people have bought the product or espoused the idea.
- 3) **Practical value:** How can we craft content that seems useful? People like to help others, so if we can show them how our products or ideas will save time, improve health, or save money they will spread the word.
- 4) **Stories:** People don't just share information, they tell stories. Information travels under the guise of idle chatter therefore messages need to be integral to the narrative that people can't tell the story without it.

- 5) **Triggers:** How are people reminded about products and ideas. Triggers are stimuli that prompt people to think about related things. People often talk about whatever comes to mind, so the more people talk about a product or idea the more it will be talked about.
- 6) **Emotions:** When we care we share. Naturally, content usually evokes some sort of emotion. In the academic field the first authors that suggested that emotion plays a key role in viral marketing, were Dobeles et al. (2007), but the first empirical study on the role of emotions in the spread of content online was that of Berger and Milkman (2012). This study had a great impact on subsequent viral marketing research and most studies that have since looked at why content spreads online also measured some type of emotion, affect, mood or valence. Jonah Berger "*What makes online content viral*" whose work was published in the association for psychological sciences put forward a theory that the sharing of stories or information may be driven in part by arousal. When people are physiologically aroused, whether due to emotional stimuli or otherwise, the autonomic nervous is activated, which then boosts social transmission. Simply put, evoking certain emotions can help increase the chance a message is shared" (Berger and Milkman, 2012). The construct was firmly established after two different experiments were conducted to test the theory that arousal promotes information sharing. In one experiment, which focused on specific emotions, 93 students completed what they were told were two unrelated studies. In the first study, students in different experimental groups watched video clips that made them either anxious or amused (high arousal emotions) or sad or content (low arousal emotions). In the second study, they were shown an emotionally neutral article and video and asked how willing they would be to share it with friends and family members. The results demonstrated that students who felt high arousal emotions were much more inclined to share with others (Berger, 2011).

To further back the theory, Berger (2013) depicted in his book "*Contagious: Why things catch on*" illustrated a real-life example of an advertorial that went "viral" after it was adjusted to evoke a user's emotions. Blendtec - a blender company posted an online YouTube video which depicted the functionality of the blender but that advert received very little views and engagement, a revised video had a sales person drop a brand new iPhone 6 plus in a blender

and have it blended, the reaction was spontaneous as the new video has so far received over 6 million views as of 26/02/2019. The video is said to have elicited an emotional response by urging users to share the video almost 16,000 times, gain almost 36,000 likes.

Figure 5 Blentec Blender



Will it Blend? - iPhone 6 Plus

6,006,682 views

👍 36K 🗨️ 4.3K ➡️ SHARE 📌 SAVE ...

Emotional aspect of a content affects whether it is shared as people will tend to share content that makes sense of their experience, reduce dissonance or deepen social connections (Berger and Milkman,2012). The key question here is which type of content is more likely to be shared, is it a positive or negative one? A study undertaken using NewYork articles indicated that content that evoked high-arousal emotions was more viral, regardless of whether those emotions were of a positive (i.e., awe) or negative (i.e., anger or anxiety) nature. Online content that evoked more of a deactivating emotion (i.e., sadness), however, was less likely to be viral.

The are other theories such as the social Identity Theory which is used to explain the different fan bases that in theory affect the level of virality due to the degree of association and inclination that guides behaviour. There is also the social sharing of emotions theory where both will briefly be discussed in the next chapter to elucidate how emotions affect individual's

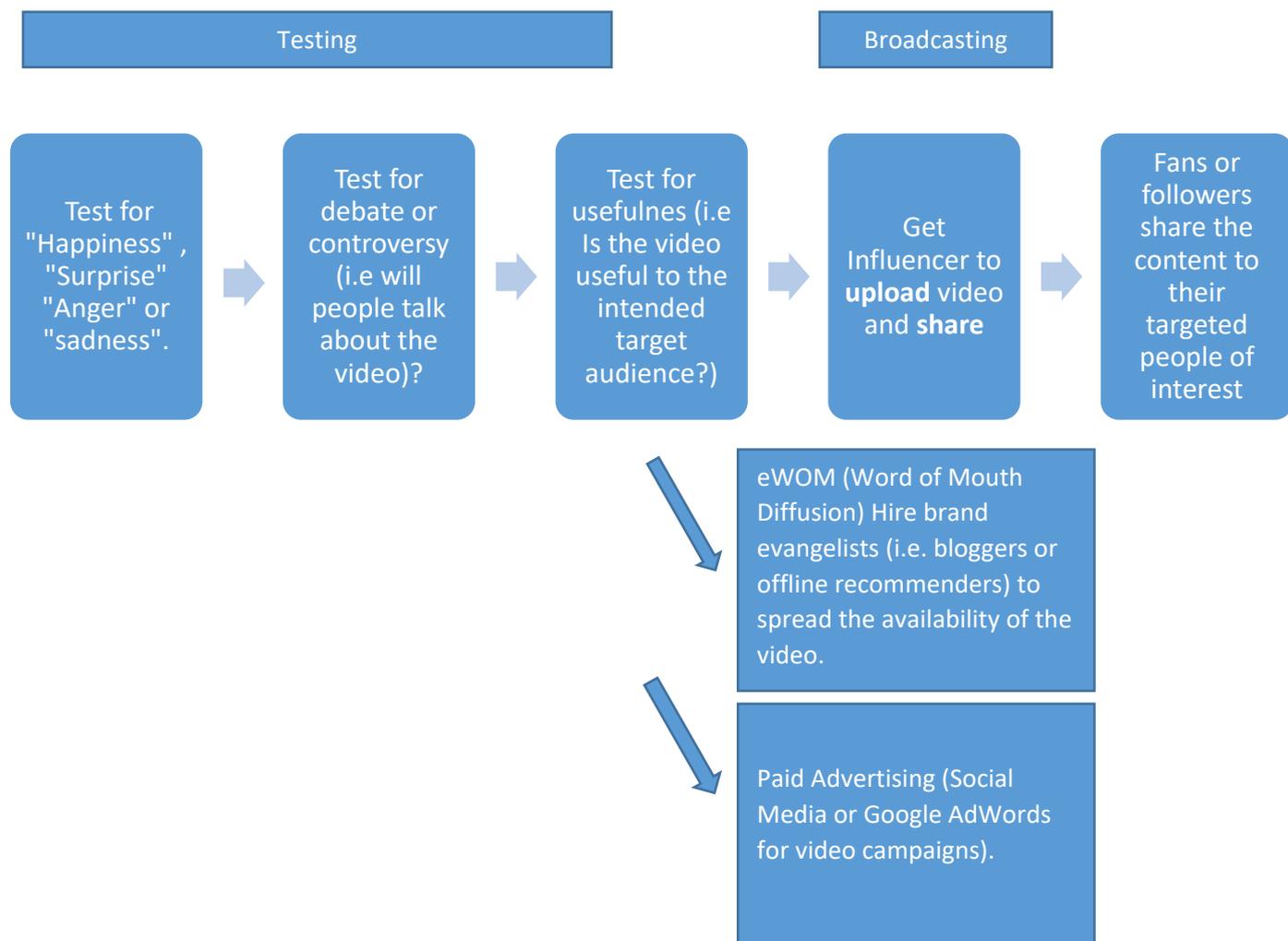
inclination to share a content , whilst the Jonah Berger STEPPS model is an extension that incorporates elements of the social sharing of emotions theory to give a broader perspective on the different kinds of emotions that can affect sharing of video content. The two theories and model are derived from the fields of Psychology and Sociology to investigate the nature of video virality. The following chapter will look at the Dual – TB model which was formulated to help further explain virality dissemination.

1.0.1.3 DUAL – TB VIRAL VIDEO MARKETING MODEL

As a video marketing practitioner who consults for Interactive video Labs which is video marketing firm there is inevitably the challenge of producing viral content for clients. A client will demand and say, “I want this content to go viral”. The key challenges are always two phased, if it’s a video produced from scratch then then it is inevitably much easier to develop a viral content as the storyboard and script can be manipulated to incorporate the emotional elements of happiness and surprise in the pre-production process through user testing which are essential for virality. Video user testing to test for virality can be utilised by doing an A/B split or Multivariate test using a variety of methods such as a focus group, web questionnaire or facial expression analysis to elicit the emotions of potential viewers. However, in some instances where the videos have already been developed it is usually less probable the video will go viral (unless it is structurally amended), it might have a burst due to the financial output but that will only be short lived and will ultimately be termed a **memoryless** or a **junk video**.

Even if a video marketer succeeds to produce a video that has high positive emotions targeted to a specific audience it is no way a hundred percent guarantee it will go viral. The reality is that there are potentially many variables (i.e seeding strategies or creative characteristics) that can influence the propensity to share apart from social groups (i.e football fans) and emotionality. To adequately consider all the variables, The Dual – TB model was devised from synthesising all aspects that instigate virality as evidenced from literature which is to be valuable for any viral video marketing campaign. The model incorporates the popularity of the uploader (influencer), electronic word of mouth (eWOM) and video paid advertising.

Figure 6 DUAL - TB MODEL



In explaining the model The videos first need to be tested for the emotional responses of “happiness and surprise” (In some cases anger). As evident from the studies videos that elicit a high level of surprise and happiness are more likely to go viral (Berger,2011; Berger and Milkman, 2012). The second phase of testing requires the marketer to test for social currency/controversy and practical value/usefulness.

Barasch and Berger (2014) hypothesise whether the mere number of people with whom consumers communicate impact what they talk about and share. Barasch and Berger (2014) argue that conversations usually involve communicating with just one person (narrowcasting), whereas others involve communicating with many people (broadcasting). The second phase of the model is the broadcasting phase which requires to have an influencer share the video using the social media (i.e such as tweet or a Facebook post), then have

another influencer retweet or reshare the post for it to get the needed traction to establish a social contagion. An alternate approach or to be used in tandem with the use of influencers is to use the eWOM (Word of Mouth). Berger (2014) explained that consumers often share opinions, news, and information with others. They chitchat about vacations, complain about movies, or rave about restaurants. They gossip about co-workers, discuss important political issues, and debate the latest sports rumours. Technologies like Facebook, Twitter, and texting have only increased the speed and ease of communication. Thousands of blogs, millions of tweets, and billions of emails are written each day. Such interpersonal communication can be described as word of mouth, or “informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers. Word of mouth includes product related discussion (e.g., a beautiful goal scored by a footballer) and sharing product related content (e.g., Nike ads on YouTube). It also includes direct recommendations (e.g., you'd love this restaurant) and mere mentions (e.g., we went to this restaurant). It includes literal word of mouth, or face-to-face discussions, as well as “word of mouse,” or online mentions and reviews. Berger (2014) notes that Word of mouth has a huge impact on consumer behaviour where Social talk generates over 3.3 billion brand impressions each day and shapes everything from the movie’s consumers watch to the websites they visit (i.e YouTube). The use of paid for advertising is an important catalyst or amplifier that can be used conjunctively to full effect if the fundamental premise of testing is done right. Some useful paid for advertising channels used by marketers comprise Google Adwords for video and social media campaigns that incorporate video.

Fundamentally, adopting an effective and robust video advertising model is important to the objectives of the marketer however there needs also to be an inherent consideration of how to gauge if the video marketing campaign is ultimately going to be successful, in this scope appropriate viral video measurement must be utilised which will be evaluated in the next chapter.

1.0.2 MEASURING VIDEO VIRALITY

Jarboe (2013) affirmed that video marketers are increasingly challenging the value of a view and instead are starting to focus on creating content and distribution strategies which drive deeper levels of engagement such as sharing, data capture, brand uplift, and online

purchases. Richard Kosinski president of Unruly said in a press release: *“Shares are the currency of social success and for leading brand marketers discovering how to create and distribute highly shareable content repeatedly and at scale is now at the top of their wish list”* (Porter, 2013). Jarboe (2013) noted that it is important that marketers create an ad that not only elicits strong emotions from consumers, but also gave its viewers a strong reason to share it with their social networks (Jarboe, 2013). However, the notion of measuring video virality is often contradicted. To support this assertion Adweek regards the number of shares as the metric to assess the virality of an online advertisement (Nudd, 2014) whilst AdAge.com (2015) highlights the number of views. Thus, it’s imperative to establish a simple metric that can be used as a basis to measure virality taking not only views into consideration but also the element of sharing in an online video environment. The currently is no metric that measures the rate at which a video is shared when viewed thus in view of this gap a standard metric has been developed known as the **Share Through Rate (STR)** which would be used to gauge the rate of virality. To devise a formula a two-phase preliminary study was undertaken with the results presented in the UKAIS (2016) conference. The first phase devised a simple formula known as the Share Through Rate with a categorisation and the second phase correlated views to shares, likes and dislikes.

1.0.2.1 METRIC FORMULATION

As explained prior the notion of virality is often contradicted and in addition there is no universally accepted and tested metric that measures the rate at which a video is shared when viewed . To highlight the problem Feder (2014) argues that the number of views as is often used by some section of marketers is insufficient to characterise virality and hence should be looked within the confines of propagation, network , speed and reach. This thesis takes a similar view point however it expands the construct to entrench the rate of propagation within the rate at which a content is shared when viewed using a Share Through Rate (STR) metric, The STR recognises the role of speed but prefers to use a taxonomy highlighting duration, it delves in-depth to discusses the role of networks within the notions of the “in and out groups” theory and lastly places the role of reach in a different segment known as popularity. **Hence, to further contribute to the gap in knowledge a metric was devised in a preliminary study known as the Share Through Rate (STR) which is used to be used partly**

as the basis to measure video virality. The basic formula that can integrate both views and shares metrics is the Share Through Rate which is basically the number of shares per viewed content as evident in the example below:

TABLE 1

YouTube Video A	YouTube Video B
Views: 100,000	Views: 200,000
Shares: 10,000	Shares: 25,000

Share through rate (STR) => shares/views

STR = S/V.

YouTube Video A

⇒ $10,000/100,000 * 100$

⇒ 10%

YouTube Video B

⇒ 12.5%

Hence Video B, has a higher virality variation by 2.5%. Even though YouTube video B has a higher viral variation the key question that will suffice is whether both videos or either video A or B have “have achieved virality”? To answer that question another important variable needs to be incorporated ,this variable which is duration determines how rapidly it takes video A or video B to attain the stated Share Through Rates. Thus, for a video content to achieve virality the video needs a 3-7 day period to attain a minimum Share Through Rate of 0.01%. As in the example above if both videos above attained the calculated Share Through Rates (STR) within 6 days then it can be attributed that both videos have gone viral. This nuanced view of virality which is to be adopted for the basis of this thesis will have its critics. The thesis position is that a time period of 1-2 days is inadequate in terms of the time lapsed to categorically imply virality due to the fact that the view count of a video which is emotionally appealing to the viewers could be gaining the needed momentum or rise in viewership as the result of non-organic factors such as a “influencer push” or “paid

advertising”, however, some marketers will disagree and argue that a video can achieve virality within the same day period or even minutes after going live. The alternate position of this thesis is that after 7 days if the video maintains the minimum threshold of 0.01% then the viral video transitions to a popular video which further falls into three categorisations which is described in-depth in the subsequent chapter.

Some marketers will question whether there needs to be a timeline in the first place to characterise virality and that only the Share Through Rate (STR) should be used as the basis at any time of the videos life span whilst others will maintain that a video can still be classed as a viral video after more than 7 days once it still maintains a constant relative views per share rate. **It is also important to emphasize that the videos adopted for this research fall within the definition criteria of achieving virality and later transitioning to become popular videos.** To further assess how the Share Through Rate formula was developed and subsequently applied see the preliminary study in Appendix A or findings which were subsequently published in the UKAIS 2016 conference proceedings (Asamoah,2016).

With the practical definition of virality being firmly rooted in this thesis, the fundamental variable of sharing needs to be further elaborated on ,more so within the context of the emotional investment of viewers in relation to football fans and non-football fans (“the in and out” groups which will elaborated further in chapter 1.3). When videos are viewed and shared, they are shared to a particular group of people who will most probably share the same interests. Feder (2014) classifies this construct as a network which is based on the tendency to share and circulation. Hence, a Manchester United football fan will share a cracking goal scored by a united player with fellow Manchester United fans on a Facebook Manchester United Page Platform. On the other hand , if the viewer of the video who is not a united fan but a football fan decides to share the video that content could be shared in a general Football page platform or will be tweeted and be retweeted by other football enthusiasts. The reach of the video will in theory be established by people who are have an affinity to Manchester united and quite possibly football fans in general (“the in group”), it is very unlikely that someone in “the out group” such as “Formula one fans” – different sports or “cooking enthusiasts” – different field of interests will have the tendency to view and share the content within their respective “in group”. To supplement this notion the diffusion of a video content as prior explained in the Jonah Berger STEPPS model and the Chohan model needs the

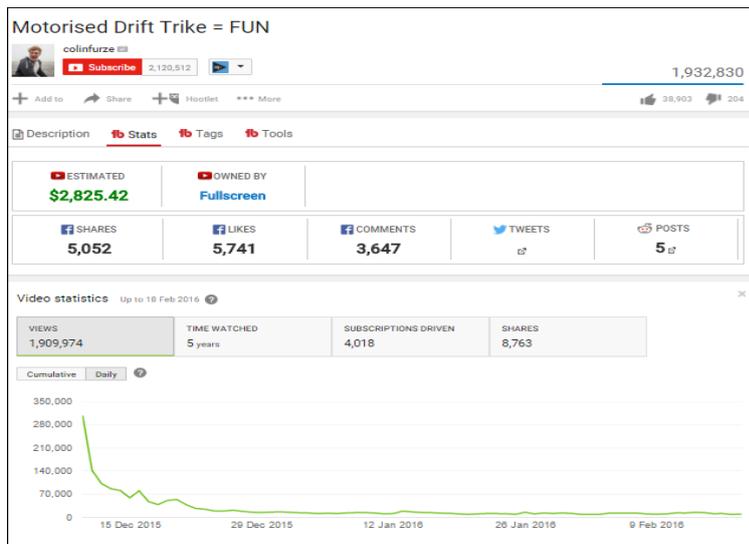
element of emotions which is the catalyst for reach or that fuel that keeps the engine running where people will share the videos time and time again within their “in-group”.

Based on the literature discussed this thesis can clearly state that a practical definition of a viral video refers to any video stimulus that has a minimum Share Through Rate (STR) of 0.01% within a 3-7 day period which is shared within a specific targeted group and has the tendency to transition to a popular video. The extent to which a video goes viral forms a fundamental part of virality research which in this research distinguishes between a viral content and a popular content. In most cases this can be used interchangeably to mean the same thing. To explain further the most popular content is also extremely viral, but equally it could be that successful products are mostly driven by mass media (i.e., a single large broadcast) or by some combination of broadcasts and word of mouth. Having discussed the various definitions of virality and video virality, the subsequent chapter will go into detail to discuss the intrinsic characteristics of popular videos.

1.0.2.2 VIDEO POPULARITY

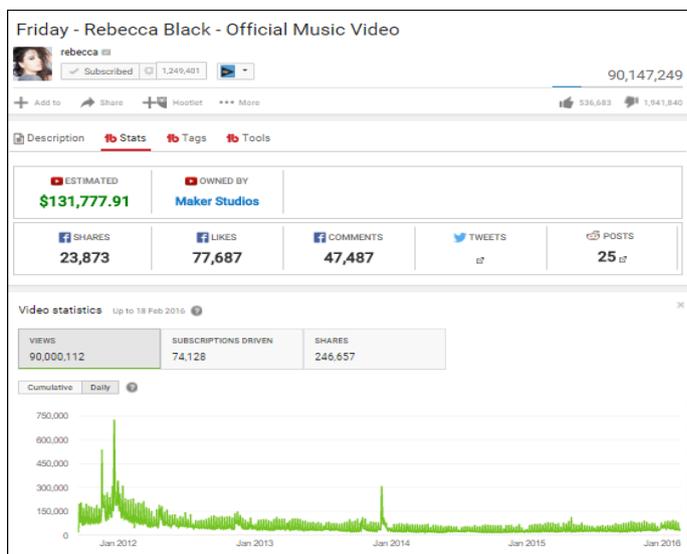
A videos popularity can be categorized into three main classes (Pinto , Almeida and Goncalves, 2013; France, Vaghefi and Zhao, 2016). **The first class of video can be classed as memoryless or initial. An “initial viral” video is usually described as a video with a large initial number of views followed by a slow decline.** Memoryless or initial videos attract little attention or experience some popularity fluctuation through a simple stochastic process. Popular viral videos experience a popularity peak that emerges through a word of mouth epidemic – internal like propagation process. Quality videos experience a very sudden peak in popularity.

Figure 7 Memoryless video



A memoryless video attains a **buzz** on the onset but fades into obscurity hardly ever reaching its initial fluctuation but goes on to accumulating very few views over time as evident from the example above. Memoryless videos are not usually backed by huge seeding and budgetary power and hence lack the adequate longevity. Seeding refers to being uploaded by a popular influencer or shared instantly by numerous individuals.

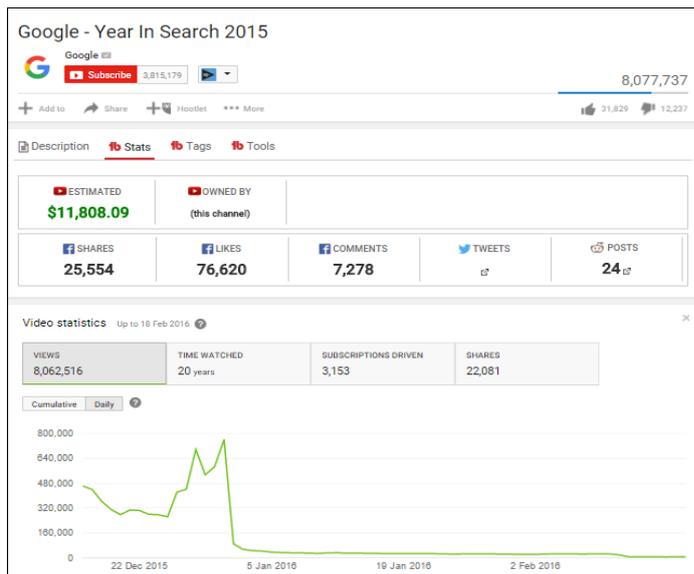
Figure 8 Popular viral video



“Popular” viral videos also known as “delayed viral” (France, Vaghefi and Zhao, 2016) experience a popularity peak that emerges through a word of mouth epidemic – internal like propagation process. The videos usually start off from a low initial base of views and then

rapidly gains popularity through viral mechanisms related to social sharing, before levelling off. Their **buzz** increases slowly up to a peak and decreasing slowly afterwards. **A viral video in its true sense is one that is also characterised by high views and shares, huge budgetary prowess and seeding strategies.** They also emotionally appeal to the audience thereby enhancing the requisite social contagion to enhance the longevity.

Figure 9 **Quality video**



Quality videos experience a very sudden peak in buzz possibly due to some external events. (Such as being featured on the first page of YouTube or due to a tweet from a high-profile celebrity) and a slow decay afterwards as users propagate the videos among themselves. They do not have very long longevity nor very robust seeding strategies. In summary, all the videos mentioned above must first meet the criteria of being a viral video and then transitioning to either one of the variants of a popular video.

Ultimately this research uses two variants of popular videos, the Memoryless and the Popular Viral Video. The memoryless video specifically is a Salford City club video which demonstrates virality in its natural phenomenistic sense and the other (popular viral video) is a viral video which is instigated with paid for advertising. The position of the thesis is that if within 1-2 days a video is seeded and instigated with non-organic means (i.e influencer or paid advertising) and continues to maintain a share through rate over a 7 day period it can still be classified as a viral video and eventually transition to a popular viral video.

The next introductory chapter will discuss the different theoretical models which were used to underpin this thesis.

1.1 THEORETICAL FRAMEWORK

The aim of this chapter is to develop a theoretical framework regarding the video virality process. This chapter is structured as follows. It begins with the explanation of existing theories, which are used to explain video virality. Three main theories that will be discussed are the **Social Identity Theory (SID)**, the **Social Sharing of Emotions Theory (SSET)** and the **Theory of Planned Behaviour (TPB)**. The **Social Capital Theory (SCT)** could have been opted as it fundamentally underpins the role of social networks however it lacked the ability to classify relationships based on “in” and “out” groups which is central to the scope of this study (i.e football fans and non-football fans).

1.2 SOCIAL IDENTITY THEORY

The Social Identity Theory was first proposed by Tajfel (1978). It is a theory that explains cognitions and behaviour of people with the help of group processes (Treppe, 2006). According to the Social Identity Theory (SIT), people tend to classify themselves and others into various social categories such as organisational memberships, religious affiliations, gender and age cohort, fans of a TV series, sporting clubs or members of a university etc. (Mael and Ashforth, 2001; Treppe,2006). Stets and Burke (2000) noted that a social identity is a person’s knowledge that he or she belongs to a social category or a group. A social group is a set of individuals who hold a common social identification or view themselves as members of the same category. Through a social comparison process, persons who are like the self and are labelled the “in-group”; persons who differ are categorized as the “out-group” (Stets and Burke, 2000). Mael and Ashforth (2001) explained that social classification serves two functions, first it cognitively segments and orders the social environment providing the individual with a systematic means of defining others. Second, social classification enables the individual to define himself.

Stets and Burke (2000) expounded that the two important processes involved in social identity formation, namely self-categorization and social comparison, produce different consequences. To define an individual’s place in the society, social categorizations are

evaluated with in comparison with other groups to get an idea of the superiority or inferiority of our group and how reasonable and adequate our “belonging to it” is (Treppe, 2006). The consequence of self-categorization is an accentuation of the perceived similarities between the self and others in-group members, and an accentuation of the perceived differences between the self and out-group members. The accentuation occurs for all the attitudes, beliefs and values, affective reactions, behavioural norms, styles of speech and other properties that are believed to be correlated with the inter-group categorization.

Some major criticisms of the social identity theory are that it can lead to an “in-group bias”. The in-group bias suggests that individuals that strongly identify with a group for example, “hard core fans” of a football team are most likely to view their group as superior to others which can lead to discrimination or favouritism. The basis of the social identity theory deals with inter-group relations – that is how people come to see themselves as members of a group or category (Stets and Burke, 2000). Having a social identity means being at one with a certain group, being like others in a certain group and seeing things from a group’s perspective. In contrast, having a role identity means acting to fulfil the expectations of the role, co-ordinating and negotiating interaction with role partners, and manipulating the environment to control the resources for which the role has a responsibility (Stets and Burke, 2000).

An aspect of Social Identity is Social validation which is the tendency for individuals to look to others to see what others are doing to determine if a behaviour is normative and appropriate (Guadagno et al., 2013). In environments where the correct course of action is ambiguous, people rely even more heavily on the cues provided by others. People are also more likely to follow the cues of others when the others are a member of their in-group and thus more like them. In a one such study, Salganik, Dodds, and Watts (2006) created a laboratory “music market” online where 14,000 participants could download songs they had never been exposed to previously. The researchers manipulated whether participants were made aware of other participants’ choice to download a song. The results of the study demonstrated that increasing cues of social validation (providing participants with knowledge of other participants’ download choices) decreased the predictability of success based on song quality. Thus, in terms of Internet videos, when one receives a forward from an in-group member, that may serve as a signal that the video is appropriate to forward to others. To contextualise

a Salford City Football fan will attend either home and away games of the team, buy the clubs paraphernalia and merchandise, watch and share football video highlights on YouTube with Salford City football fans who have a strong inclination to associate with the ideals and do likewise. Such a strong inclination to identify and participate within an emotional context can be further explained using the social sharing of emotions theory as seen below.

1.3 SOCIAL SHARING OF EMOTIONS THEORY

After people have experienced an emotional response to content, they consider the option of passing the content on to their social networks (Feder, 2014). Rime (2009) shows that when people have emotional episodes they tend to interact socially. The Social Sharing of Emotion theory explains why people aim to connect with others after emotional experiences, and how this sharing of emotional content, in turn, causes emotional reactions in others (Christophe and Rime, 1997). Online social networks provide viewers with an immediate avenue to socially share the emotions that were elicited by the content. Viral marketing authors contend that there are various social reasons why people share content online: to increase their status (Chu, 2011; Lagger, lux and marques, 2011; Roy, 2011), out of altruism (Phelps et al., 2004; Roy, 2011), to allow others to laugh (Lagger, lux and marques, 2011; Roy, 2011), to inform others (Lagger, lux and marques, 2011), or for economic incentives (Roy, 2011). However, authors disagree about which specific social reasons drive the sharing of content online. These social motivations for the spread of content online need further investigation especially within a theoretical context.

Rime et al. (1992) explored the phenomenon as to whether people share their emotions, whether they do it more readily than others, how often and with whom they speak about such experiences. The findings showed that most emotional experiences are shared with others shortly after they have occurred, and that social sharing of emotions represents an integral part of emotional experiences. Wagner et al. (2014) supported the stance to explain that one of the most fundamental characteristics of human beings is their social nature where there is a need to form social bonds to share experiences. By socially sharing their experiences individuals can modify their subjective perceptions of these experiences in a positive manner. Wagner et al. (2014) illustrated that when people go to the cinema, they rarely do so alone but in most cases go together with a partner or a friend. Apart from expecting to be

emotionally moved by the film itself, they anticipate a positive impact of sharing this emotional experience with a peer, even though both are passively watching an event and there are only minimal opportunities to talk to each other during the viewing.

Elaborating on the premises, Rime et al. (1998) pointed out that the phenomena studied by the psychology of emotion – joy, anger, fear, sadness, shame and the like are characterized by a sudden disruption of a people’s subjective world. Research findings from Rime et al. (1992) showed that emotional experiences are shared in 86 -88% of the cases with the extent of the sharing related to people who were intimates (i.e. parents, close family members, best friends, spouse or companions). Further studies reveal that a marketing message from a friend (i.e a video) instead of a commercial source may reduce resistance toward the commercial message and make people more receptive of the message content where the strength of the relationship with the sender of the message also positively influences pass-on intentions (Ketelaar et al.,2016). For example, a football fan will more likely pass a football related video to a football community on Facebook where the social ties are stronger (Chu and Kim, 2011) thereby the video being watched and shared by other football fans.

1.4 RESEARCH PROBLEM DEFINITION

The main motivation for undertaking this research is related to understanding what causes online videos such as the one in figure 1 to go viral. The rise of YouTube combined with improved sharing functionality across most social networking sites, has paved the role of viral video in the marketing mix of many corporates (Eckler and Bolls, 2011; Jiang et al.,2014). When executed correctly, a viral video campaign is said to offer the marketer benefits such as extended campaign reach, reduced advertising avoidance and increase in earned publicity for the brand (Broxton et al., 2013; Jiang et al., 2014). because viral marketing research is still in its early stages, most of research is concerned with the motivations and behaviours of those passing along content (Cruz and Fill, 2008). However, there is no archetype that academics can draw upon to better understand the sharing of content online. Watts , Duncan and Paretti (2007) state that, “as appealing as a viral model of marketing seems in theory, its practical implication is greatly complicated by its low success rate”. It is evident that researchers remain unclear as to what drives the spread of content online. These limits support the call for research on what makes online video content to go viral.

By explaining the problem definition, it will be prudent to identify the aim and objectives of this research next.

1.5 AIM AND OBJECTIVES

The main aim of the research is to understand what emotions affect online videos in going viral.

The following are the objectives of the current research:

- 1) **To understand if viral videos are characterised by specific emotions and are affected by a fan group dynamic:** There have been some contemporary studies on what emotion(s) constitute virality. Some academic researchers such as Jonah Berger theorise that the emotional element of surprise is important whilst others such as Nelson-Field and Dobele argue that is happiness. Other researchers such as Guandago also theorise that social groups (I.e Fan groups such as football fans and non-football fans) also affect virality. Inevitably, this research will use the facial expression analysis tool which has not been used prior to either support or advance our current understanding of which emotions characterise virality as well as the intention to share.
- 2) **To develop a unique method for predicting an online video:** There are two categories of prediction models, the most prominent ones require the use of historical statistical algorithms to predict to what extent a video can go viral whilst less known but more current use automatic or real-time models to predict online virality of UGC (User Generated Content). The new experimental approach developed for this research does not require any historical data as it relies on the emotionality elicited from the viewers which can be represented using a mean distribution curve. Other works worthy of reference which uses real time approaches for predicting emotions based on video content analysis include the mid-level concept feature and computational approaches which rely on complex data segmentation and extraction models (Ellis et al.,2014; Jiang, Xu and Xue,2014; Jou, Bhattacharya and Chang, 2014). This thesis on the other hand uses **facial expression analysis** which arguably provides a more robust and efficient way of eliciting and collating the emotional responses of its subject participants. Thus, the new approach adopted for this thesis will enhance our

understanding of real time predictive models by providing further insight into the structure of real time modelling as well as comparing the different real time and historical predictive approaches that can be used by marketers and researchers for predictive modelling.

- 3) **To find an effective method for measuring users' emotional intensity when watching a video stimulus:** A secondary and an interlinked part of this study will be to evaluate methods that are used by researchers to measure emotions elicited on users who view a viral video content. The two methods selected for the study is the use of the facial expression analysis tool and an online web questionnaire survey. Though previous research has shown the validity on the use of the facial expression analysis tool the use of the questionnaire survey is not well documented and thus will be the validating criterion. It is also important to establish a preamble for the limitations of the FaceReader technology particularly in relation to data bias stemming from age, gender or race or process of analysis with micro-emotions.

It is also important to recognise the limitations of the technology as a whole , current studies have shown that the FaceReader is an efficient tool for analysing emotions with an accuracy of 90% (Yu and Ko,2017). Though 90% from the outlook may seem large the 10% variability is significant when taking into consideration the robust measurements in relation to demographic segments such as race, age and gender which can ultimately lead to data bias. The limitations of measuring emotions leading to data bias is significant as there are a varied examples of limitations within emotion recognitions systems, for example, Google facial recognition system labelled black people as Gorillas (Barr,2015), the cameras of a phone NikonS630 identified Asian people as blinking whilst in reality they portrayed their natural appearance with subtle smiles (Lee, 2009). To expand on this point a study done using two emotion recognition systems (Face++ and Microsoft Face API) indicated that on average black faces occur twice as angry as white faces whilst black faces were three times more contemptuous hence weighing negative emotions to a specific race (Rhue, 2019). There is also the subject of gender misidentification which supposedly occurs in a higher rate among people of colour (Lohr, 2018).

Another significant limitation of the FaceReader is that it is restricted to 6 basic emotions plus neutral and more complex emotions cannot be analysed (Yu and Ko, 2017) – some current versions also include “contempt” as the 7th emotion. A previous study found the participants began the experimental task with seriousness, but FaceReader explained their emotion as anger. The findings outlined above have proved that FaceReader can objectively detect immediate and subtle changes in facial expressions, and arrives at judgments based on potentially representative components of emotions with high accuracy rate. Nevertheless, researchers’ observations and participants’ oral responses are required for understanding the participants’ feelings and for further discussion on the results of facial expression recognition. This is very important and will be highlighted further in the methodology section.

The next chapter will provide insight into what gaps exist in the research and the approach that will be taken to solve it.

1.5.1 RESEARCH QUESTIONS

Oats (2006) highlighted the importance of incorporating research questions into any research study for the development of a research hypothesis and in defining objectives. Saunders, Thornhill and Lewis (2009) argued that research questions should be agile, and crafted to flow along with the study. Based on a review of the existing literature, discussions, conference presentations and empirical data collection, the research questions were formulated and modified using a deductive approach as the project progressed to settle on the questions outlined below. Furthermore, the research questions were used as fundamental basis to ascertain if the research adequately contributed to existing knowledge in the concluding chapter.

Based on the AIM and objectives of the thesis the following research questions can be formulated.

Question 1: What is the practical definition of virality within the context of online videos?

This study holistically looks into what fundamentally defines a viral video through the synthesis of existing literature and devising a standard formula.

Question 2: What emotions drive the virality of online video content?

This study takes an in-depth look at the role that emotion plays in the sharing of content online. Because there is disparity in the literature regarding whether valence, affect in general, or specific emotions should be studied in this context, this question takes a broad-based approach and looks at emotions in general. After better understanding the fundamental role that emotion plays in the sharing of content online, the interplay between content and emotion can be further explored into finding out if some emotions tend to help diffuse online videos more than others.

Question 3: What is the unique way of predicting user emotions from online videos?

The study aims to explore a unique way of predicting user emotions from online videos in real time.

Question 4: What is a more effective method for measuring users emotions when watching a video stimulus when comparing facial expression analysis and self-report?

The study takes an exploratory approach to establish if both or one of the methods are effective for measuring emotions elicited from watching a video stimulus which will significantly add to the body of the knowledge.

1.5.2 APPROACH TO SOLVE THE GAPS IN LITERATURE

The purpose of this section is to explore the gaps in literature, understand the objectives and devise an approach to address the gaps.

TABLE 1

GAPS TABLE

RESEARCH PROBLEMS	OBJECTIVES	APPROACH TO ADDRESS THE PROBLEMS
<p>1. Lack of understanding of which emotions characterise virality as well as the effect of fan groups, arousal and emotions on the intention to share.</p>	<p>Objective 1:</p>	<ol style="list-style-type: none"> 1. An in-depth review and synthesis of existing theories on sharing. 2. Facial expression analysis testing. 3. Data analysis using t-test.
<p>2. Investigating a unique method for predicting online videos.</p>	<p>Objective 2:</p>	<ol style="list-style-type: none"> 1. Research on existing models used to predict virality. 2. A review and utilisation of normal distribution bell curves. 3. Quantitative research using facial expression analysis data.
<p>3. Lack of an effective method for evaluating user's emotions in viral videos.</p>	<p>Objective 3:</p>	<ol style="list-style-type: none"> 1. Quantitative research using correlation coefficient analysis of emotions data obtained from facial expression analysis and questionnaire survey to test for discriminant validity.

--	--	--

1.6 THESIS STRUCTURE

This thesis is organised into six chapters: Introduction, Literature Review, Methodology, Results (Analysis), Discussion and Findings, and Conclusion & Future Research.

Chapter One - Introduction:

An establishment of the background and motivation pertaining to the study. Additionally, it seeks to introduce the reader to the concepts of virality through provision of the definitions pertaining to the study that introduces the subject.

Chapter Two – Literature Review:

A structured review of previous studies covered by previous authors pertaining to the topic. The literature review within this study first and foremost investigates the concept of emotions and facial expressions pertaining to the ideas of Paul Ekman. Subsequently, the chapter provides a deeper analysis of the aspects that enhance our further understanding of virality and its relation to emotions through the lens of Jonah Berger who is an authority on the subject.

Chapter Three - Methodology:

This section provides a justification for the study that identifies the research methods utilised within the study. It further justifies the research strategy utilised for collection of the data required within the study. This chapter also provides justification pertaining to the chosen research method utilised within the study. Moreover, there is an incorporation of the exploratory phase pertaining to the quantitative method and the research design adopted. This enhances the research process rendering it more effective and efficient due to inclusion of readily measurable elements.

Chapter Four – Analysis:

Research Finding 1

There is an analysis of the results derived from the data collected from the online survey and facial expression analysis. Also, it provides statistical data analysis on the data discussed

through the utilisation of graphs and charts. More importantly it goes on to further provide evidence for the hypothesis tests derived from the conceptual framework (see 2.5.1). *The findings section was divided into three segments, with segment A focusing on the variations associated with viral video groups and fan group dynamics, segment B focusing on the intention to share video content online and segment C an analysis of triggers which depict when videos are most likely to elicit sharing behaviour.*

Research Finding 2

The second analysis takes existing data from facial expression analysis to enhance our understanding of elicited emotional patterns which can be used as a model to predict and characterise a viral content.

Research Finding 3

Finally, the research compares two methods (Facial expression analysis and Questionnaire) and undertakes a discriminant validity test to assess which method is best suited for measuring intrinsic emotions.

Chapter Five – Discussion

This chapter provides a discussion and analysis of the result found from each of the research findings as well as those identified in Chapter 2 – The Literature Review. An analysis of the research findings in this chapter seeks to identify the information retrieved within the study pertaining to the research questions and objectives developed in relation to the study.

Chapter Six – Conclusion & Future Research:

A clear representation of the main findings of the thesis in relation to the thesis contribution to knowledge based on the research questions and hypothesis of the thesis. This chapter also gives a synopsis of future research that can be undertaken from the study.

2.0 LITERATURE REVIEW

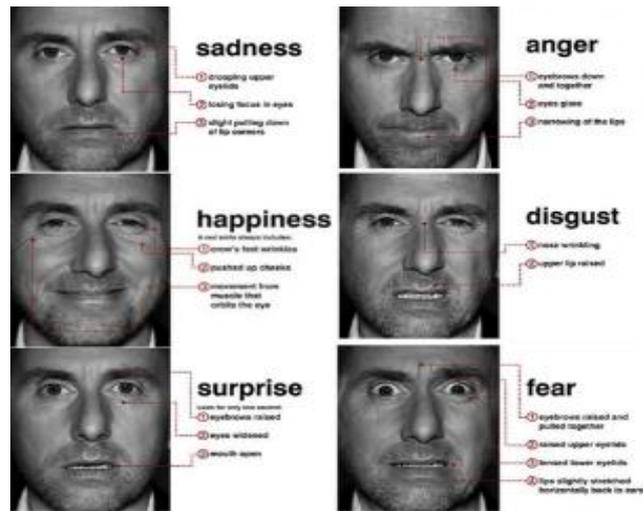
The aim of the literature review section is to describe how the proposed research is related to prior research undertaken and relevance of the research problem. The literature review will inevitably aid in providing the justification for the chosen methodology.

The previous chapter introduced the research problem area as well as the aim and objectives of this study which is related to the previous studies. This literature review will holistically look at the concepts of emotions, facial expressions and the viral phenomenon which is described throughout this chapter.

2.1 WHAT ARE BASIC EMOTIONS?

There is debate as to whether there is a set of basic emotions and how to measure them (Ekman and Davidson, 1994). However, there is a group of named feelings which are often referred to as basic or primary emotions that can be reliably tested (Ekman, 1994; Evans, 2001). There is also the debate about exactly how many there are and the precise names for them. The emotion annotation and representation language (EARL) proposed by the Human-Machine Interaction Network on Emotion (HUMAINE) classifies 48 emotions (Emotion – Research ,2006). Through years of studying emotions, Dr. Robert Plutchik, an American psychologist, proposed that there are eight primary emotions that serve as the foundation for all others: joy, sadness, acceptance, disgust, fear, anger, surprise and anticipation. Plutchik’s (1980) approach to defining the structure of emotions has, however, been subject to criticism from various authors (Ortony and Turner, 1990; Richins, 1997). It is important to explain that the emotions identified by Plutchik are opposites, therein, depicting joy and sadness, acceptance and disgust, fear and anger, surprise and anticipation (Heuvel, 2017). The key criticism of the Plutchik’s (1980) model of emotion is that it cannot easily facilitate the measurement of non-primary emotions, such as satisfaction or delight. This study however will focus on the emotions proposed by renowned emotion Psychologist - Paul Ekman. It has been argued that different words may just describe different levels of intensity of the same emotion, for example “joy” and “elation”. Different emotions can be experienced simultaneously, such as Norman’s (2004) rollercoaster example where people are both excited and anxious. While these basic emotions may not be a definitive list of feelings experienced by everyone worldwide, they serve a purpose in allowing better communication of our experience (Cameron-Bandler and Lebeau, 1986). Paul Ekman (1992) defined 6 basic emotions as sadness, happiness, surprise , anger, disgust and fear which is depicted below:

Figure 10 **Basic Emotions**



It is important to note that within the context of emotions, the autonomic response to unexpected stimuli (e.g. doors slamming, spiders, roller coaster rides, snakes etc) involves an increased heart rate, sweaty palms, and irregular or faster breathing which readies us for action. In response to perceived threats, our body readies us for flight from, or fighting with, the perceived threat (Evans, 2001). Furthermore, a theory of individual feelings can provide names, valence, level of arousal, the cause, expression, whether it was culture specific or innate, basic or higher cognitive, the signal and action and the individual physiological markers. Unfortunately, research tends to focus on basic emotions such as fear, anger and sadness rather than all possible emotions (Ekman, 1994). This may be an outcome of the lack of agreement of what basic emotions are. Specific words used to describe feelings often differ in different cultures, differ across time and even in different social groups within a culture. “Happy” can also be referred to as “joyful”. The nuances of “feeling words” highlight how difficult they are to quantify. While agreement on feelings is not unanimous it seems clear that there are several basic emotions with many derivatives. Thus, the understanding of the scope of emotions is important within this research to help us understand our human facial expressions.

2.2 FACIAL ACTION CODING SYSTEM (FACS)

Bartlett et al. (2014) define **Facial Action Coding System (FACS)** as a method developed by Paul Ekman, Wallace Friesen, and Joseph Hager to identify specific changes to facial expressions that occur with muscular contractions and quantify how the contraction of each facial muscle (singly and in combination with other muscles) changes the appearance of the face. Bartlett et al. (2014) explain that changes in the appearance of the face are associated

with the action of muscles that produce them to create a reliable means for determining the category or categories in which each facial behaviour belongs. Cohn, Ambader and Ekman (2007) explicate further that FACS observations are quantified in measurement units known as Action Units (AUS). Some facial appearances include motions of more than one muscle whose effects on observed changes in facial appearance are not readily distinguishable. In other instances, the relatively independent actions of different parts of the same muscle or muscles participate in distinct facial actions. Using FACS, an observed facial expression or action is decomposed into the specific AUS that produced the movement. Action units, with some qualifications, are the smallest visually discriminable facial movements. By comparison, other systems are less thorough and fail to differentiate between some anatomically distinct movements (Cohn, Ambader and Ekman, 2007).

Ramachandran (2012) notes that human coders can manually code nearly any anatomically possible facial expression, deconstructing it into the specific action units (AU) and their temporal segments that produced the expression. As AUs are independent of any interpretation, they can be used for any higher order decision making process including recognition of basic emotions, or pre-programmed commands for an ambient intelligent environment. Sayette et al.(2001) argued that a criticism of FACS is that the Psychometric knowledge of FACS has not kept pace with the increasing and multiple uses of FACS coding in emotion science and related fields and in changes in FACS over time. While a proficiency test is required for certification as a FACS coder, relatively little information is available about the reliability of FACS coding for individual AUs and related measures (e.g., AUs intensity), especially for the use of FACS with spontaneous facial expression. Thus, it is unwise to assume that good reliability for these measures in posed expression indicates good reliability in spontaneous expressions. Spontaneous expressions are believed to differ from voluntary ones in both their morphology and dynamics, including velocity and smoothness of motion (Sayette et al.,2001) In addition, rigid head motion and face occlusion, which can impede coding are more likely to occur during spontaneous expressions. To accommodate the greater range of head motion found in studies of spontaneous expression, investigators often use wider camera angles, which reduces face size relative to the video frame and makes coding of subtle motion more difficult. Furthermore, The FACS certification test requires coders to score videotapes of spontaneous expression with a high level of agreement with a group of reference coders. Consequently all FACS-certified coders presumably have achieved

reliability. Nevertheless, many published studies of spontaneous expression either fail to report FACS reliability or provide only incomplete information (Sayette et al., 2001). It is important to test whether the reliability achieved for FACS certification is maintained in research studies. Another issue is that FACS fails to measure expressions in real time and other models are needed to address the gap (Gupta, 2018).

Farnsworth (2019) recognises that the analysis of facial expressions is one of very few techniques available for assessing emotions in real-time whilst (fEMG) is another option. Other measures, such as interviews and psychometric tests, must be completed after a stimulus has been presented. This delay ultimately adds another barrier to measuring how a participant truly feels in direct response to a stimulus. Researchers have for a long time been limited to manually coding video recordings of participants according to the action units described by the FACS. This process is now possible to complete with **automatic facial expression analysis**. This saves vast amounts of time and money, as scoring no longer requires analysis of each frame by a trained researcher – the software such as the Noldus 6 FaceReader which was used in this thesis does the work for the researcher.

2.3 WHAT ARE FACIAL EXPRESSIONS?

The origins of facial expression analysis go back into the 19th century, when Darwin originally proposed the concept of universal facial expressions in man and animals. Since the early 1970s, Ekman and Friesen (1975) have performed extensive studies of human facial expressions, providing evidence to support this “universality theory”. These ‘universal facial expressions’ are those representing happiness, sadness, anger, fear, surprise, and disgust. To prove this, they provide results from studying facial expressions in different cultures, even primitive or isolated ones. These studies show that the processes of expression and recognition of emotions on the face are common enough, despite differences imposed by social rules. Ekman and Friesen used **FACS (Facial Action Coding System)** to manually describe facial expressions, using still images of, usually extreme, facial expressions. This work inspired researchers to analyse facial expressions by tracking prominent facial features or measuring the amount of facial movement, usually relying on the ‘universal expressions’ or a defined subset of them. In the 1990s, automatic facial expression analysis research gained much interest, mainly thanks to progress, in the related fields such as image processing (face

detection, tracking and recognition) and the increasing availability of relatively cheap computational power.

According to Mauss and Robinson (2009) Facial behaviours appear to reliably indicate the valence of a person's emotional state. For example, Duchenne ("non-social") smiles involving wrinkling of the muscles around the eyes have often been linked to experiences of positive emotion. By contrast, negative emotion inductions are often associated with a visible facial behaviour in which the eyebrows are lowered and brought closer together. In a study using a more molar facial action coding system, Mauss et al. (2005) found strikingly large correlations between valence and the person's facial behaviours, $r_s > .80$. Studies have shown that face identity is better recognised from dynamic than static displays when the stimuli are degraded (e.g., shown as negatives, upside down, thresholded, pixilated, or blurred). However, the advantage disappears with unmodified stimuli. In short, insofar as recognition of identity from complete static images is already close to perfect, motion appears to be beneficial only when static information is insufficient or has been manipulated (Mauss and Robinson, 2009).

All studies summarised so far indicate that dynamic information is a significant component of our representation of facial expressions (FEs). However, they do not provide evidence that bears directly on the dynamic advantage hypothesis. Such evidence emerges instead from a third group of studies comparing emotion identification under static and dynamic conditions. Harwood, Hall, and Shinkfield (1999) tested identification in healthy observers and patients with mental retardation. Dynamic stimuli were twelve FEs of the six basic emotions (anger, disgust, fear, happiness, sadness, and surprise) posed with average intensity by one male actor and one female actor and recorded from neutral through the expression's completion; static stimuli were the same displays frozen at the apex. Both groups identified sadness and anger significantly better from dynamic than from static displays, but the advantage was limited to just these two emotions.

2.3.1 WHAT IS FACIAL EXPRESSION ANALYSIS?

Kuilenberg, Wiering and Uyl (2005) noted that apart from the means to identify other members of the species the human face provides several signals essential for inter-personal communication in our social life, personality, attractiveness, age and gender can also be seen from someone's face. Thus, the face is a multi-signal sender or receiver capable of

tremendous flexibility and specificity. In turn, automating the analysis of facial signals would be highly beneficial for fields as diverse as security, behavioural science, medicine, communication, education, and human-machine interaction. Facial expression instruments are based on theories that link expression features to distinct emotions. Examples of such theories are the **Facial Action Coding System (Ekman and Friesen 1978)**, and the **Maximally Discriminative Facial Moving Coding System (Izard, 1990)**. Generally, visible expressions captured on stills or short video sequences are analysed. An example is the Facial Expression Analysis Tool. According to Ioannou et al., (2005) Facial features and expressions are critical to everyday communication. Besides speaker recognition, face assists several cognitive tasks: for example, the shape and motion of lips forming visemes can contribute greatly to speech comprehension in a noisy environment. While intuition may imply otherwise, social psychology research has shown that conveying messages in meaningful conversations can be dominated by facial expressions, and not spoken words. This result has led to renewed interest in detecting and analysing facial expressions in not just extreme situations, but also in everyday human-human discourse. A very important requirement for facial expression recognition is that all processes therein must be performed without or with the least possible user intervention. This typically involves initial detection of face, extraction and tracking of relevant facial information, and facial expression classification.

There is evidence that supports the existence of a few recognized facial expressions for emotion such as happiness, surprise, fear, sadness and disgust (Ekman, 1982). Hence estimating emotional experiences from objectively measured facial expressions has become an intrinsic part of emotion research. Facial expression has also been extensively used in emotion research (e.g. Choliz and Fernandez-Abascal, 2012; Jackson et al., 2015) however, there are problems with measuring facial expression when participants are interacting with a computer rather than a person. Despite the findings of Reeves and Nass (1996), people do not always respond the same when looking at a computer screen. In spite of the limitation this research will place emphasis on the use of facial expression analysis to understand user's emotions on viral videos using the FaceReader 6 platform to undertake an adequate meta-analysis and enhance the methodological triangulation process with the web-questionnaire to gain a holistic understanding of user's emotions.

2.3.2 NEGATING FACTORS IN FACIAL EXPRESSIONS

The limitations of the FaceReader technology can originate not just from the technological artefact but more significantly from the people depicting facial expressions. One important factor that must be considered is the issue of control as we cannot always control our emotionality (Slepian and Carr, 2019; Carr,2019). The question then is whether control is requisite in a controlled experimental environment and to what degree both the subject and the officiator can have an effect on the test. To expatiate, some participants who partake in a facial expression of emotions study are likely to have calibration issues with the Face before the start of the actual facial expression analysis test. Due to the issues the Subject participants are likely to show physical attributes of anxiety and anger which will inherently have had an impact on the actual testing when the participants will be viewing the video stimulus. The anxiety or anger was primarily clearly evident within this research where it was noted that participants who undertook the study in the laboratory setting showed a higher degree of anger as opposed to those who undertook the study in a remote environment (p.122-123).

In context with the scenario above Paul Ekman's work is pivotal in explaining the role of emotions to the scope of the study. Most pertinent to this research encompass how individuals differ in the facial expression of emotions. Facial expressions reflect "**affective states**" and therefore possibly predict associated behaviour and attitude change (Friesen and Ekman, 1983). Facial expressions of emotions are semi-universal sequences of facial muscle contractions linked with the emotional state of the person. The neuro-cultural theory of emotion, which is advocated by Ekman (e.g. Ekman, 1972) defines facial expressions of emotion as discrete, innate and culturally independent. Ekman (1992) posits that there are several separate emotions which differ from each other with evolution playing an important role in shaping both their unique and important features. Ekman (1992) argues that the strongest evidence for distinguishing one emotion from another comes from research on facial expressions as there is robust, consistent evidence of a distinctive, universal facial expression of anger, fear, enjoyment, sadness and disgust. Ekman (1970) found concrete evidence that there exists a universal facial expression of emotions after comparing students in the USA and Japan eliciting the same emotions whilst watching the same video stimuli. The findings provided conclusive evidence that there is a pan-cultural element in the facial

expression of **emotions**. However, New research is challenging the main pillars of basic emotion theory propounded by Ekman. First is the idea that some emotions are universally shared and recognised. The universality of facial expressions was first challenged by Russel a staunch critic of Ekman's work. Particularly, with merit is an insight to a rebuttal where Paul Ekman goes into detail espousing the major inaccuracies that were published by Russel. Russell (1994) argued that only certain facial patterns are the manifestations of the same emotions in all human beings where observers everywhere attribute the same emotional meaning to those facial patterns. Ekman (1994) argues that by limiting the universality position, the first related to how emotions are shown in the face and the second to how the emotional meaning of expression is judged and by failing to include how facial expressions vary with culture, Russel created a false basis for what to expect in cross cultural studies of judgement of facial expressions. Ekman (1994) maintains that it is wrong for researchers to expect perfect agreement within each culture and perfect correspondence among cultures, with no exceptions of deviations. Presumptuously, the same erroneous notion of "perfect agreement" seems to be depicted in more contemporary studies on the universality of emotions which tends to contradict the studies undertaken by Paul Ekman. **For example,** Crivelli and Fridlund (2018) depicted an experiment which showed Trobriand Islanders photographs of the standard Western face of fear – wide-eyed, mouth agape – and asked them to identify what they saw. The Trobrianders didn't see a frightened face. Instead, they saw an indication of threat and aggression. The conclusion is that what we think of as a universal expression of fear isn't universal at all. But if Trobrianders have a different interpretation of facial expressions, what does that mean? Meyers (2019) asserts that one emerging – and increasingly supported – theory is that facial expressions don't reflect our feelings but instead of reliable readouts of our emotional states, they show our intentions and social goals. Crivelli and Fridlund (2018) supported the argument by insisting that previous research was systematically flawed where prior support for the neuro-cultural or universality thesis rested mostly on using null hypothesis significance testing in matching-to-sample experiments, using posed face photos and emotion labels or stories. Although the few tests of the thesis reported overall matching scores of roughly 50%, the results have been touted consistently as proving universality. Excluding chance in the way participants responded to the tasks (i.e., rejecting the null hypothesis) became the standard criterion for claiming universality, regardless of the magnitude of the effect. In addition, Crivelli and

Fridlund (2018) argued that new studies showed that in many emotion categories considered 'basic' (e.g., anger, fear, disgust), respondents fared poorly by expectations. Indigenous respondents attributed disparate meanings to facial displays when isolated from context. For example, although Western participants clearly believe that a smiling face reflects happiness, Trobrianders instead associate smiling with behaviours (laughing), Trobriand emotions (mwamwasila; magic of attraction, radiance), or dimensional affective properties such as valence (kalalumkola bwena, feeling good). Despite the new research that appears to discredit universality, this thesis assumes a middle-ground approach, by so doing it used a varied range of participants comprising ethno-demographics from different racial groups and countries of origin. The FaceReader which was a tool used for measuring facial expressions had some difficulties in some instances calibrating the facial muscles and their respected emotions with people of dark colour.

The Second argument against Paul Ekman is the belief that facial expressions are reliable reflectors of these emotions. Ekman (1993) inquired whether emotions can exist without facial expressions. Ekman (1993) noted that there is evidence that people may show no change in visible facial activity which contrasts with Tomkins (1963) proposal that facial activity is always part of an emotion even though they report feeling emotions and manifest symptoms in the autonomic nervous system activity. This research did not determine, however, whether there might be people who show no facial activity at all visibly or non-visibly, when there is subjective or physiological evidence of emotion. Ekman (1993) argued that apart from the fact that some individuals are not facially active, there may be ways of calling emotions that are less likely to generate a facial expression. This usually occurs when someone sees or hears a dynamic event and the beginning of the event is marked rather than very small and gradual. Albeit, Ekman (1993) noted that facial expressions can contradict what a person is saying or what observers believe to be normative in a situation. Ekman (1993) argued that people can fabricate expressions when do not feel any emotion. In a false expression, a face is made to mislead the observer into thinking that an emotion is felt when it is not. There is evidence to suggest that false expressions can be distinguished from genuine expressions by the absence of certain facial muscular actions which cannot be performed voluntarily with anger, sadness and fear being some of them. Ekman (1993) depicted the presence of mock expressions which state that the person feels the opposite of the emotion

shown. For example, when describing a situation which is not amusing at all, the expressor may show an exaggerated smile, perhaps also laughing in a deliberately false fashion, underlying the point that was not experienced. The facial expression tool which was used as part of this study has the capability to detect mock facial expressions to a certain degree of accuracy as it relies on accurately measuring facial muscles (See Terzis, Moridis and Economides, 2011). Carroll and Russell (1996) delineated a distinct viewpoint where the researchers felt that though the face provides information relevant to information it does not necessarily signal a specific emotion. On the contrary, Paul Ekman's case for postulating a correlation between facial expressions and emotions has been supported using lab experiments by other researchers with tools such as the FaceReader which is able to measure human emotions from "facial expressions" with an efficacy of over 87%, Specifically, where the rates of agreement are as high as 90% for a "happy" expression and as low as 70% for a "disgusted" expression and 71% for an "angry" expression (Terzis, Morides and Economides,2011). In another study D'arcey (2013) found preliminary evidence that the FaceReader is a valid measure of happy, angry, disgusted and sad expressions when it validated the use of the FaceReader with the use of facial EMG(Electromyography) and Lewinski et al. (2014) noted that Facial expressions of happiness – automatically analysed by FaceReader - can reliably distinguish between amusing and non-amusing video advertisements. In addition, Mauss et al. (2005) found large associations between valence and the person's facial behaviours using the FaceReader.

Consequently, Ekman (1993) asserted that if a language has no emotion as has been reported by some anthropologist, it does not mean that emotion does not occur in that culture, only that it is not represented by single terms in the lexicon. Levy (1984) argued that although Tahitians have no word for sadness, they witnessed sad expressions in people. This view is shared by contemporary research which also supports the idea where the findings suggest that understanding emotional signals is not based on the words, we have in the language to describe emotions but instead emotions appear to have evolved as a set of basic human mechanisms (Sauter, LeGuen and Haun, 2011). It is in this regard that the facial expression analysis tool will be a more robust fit as it will not require participants audibility to measure their emotions.

Having discussed in-depth the negating factors that can occur in facial expression analysis the subsequent chapter will go on further to discuss the phenomenon of micro-expressions and suppressions.

2.3.2.1 MICRO EXPRESSIONS AND SUPPRESSION

Facial micro-expressions are rapid involuntary facial expressions which reveal suppressed affect (Pfister et al.,2011). Wu et al.,(2018) explained that humans are good at recognising full facial expressions which present a rich source of affective information. However, psychological studies have shown that affect also manifests itself as **micro-expressions**. These are very rapid (1/3 to 1/25 second; the precise length definition varies - **these involuntary facial expressions give a brief glimpse to feelings that people undergo but try not to express**. To elaborate, Goman (2015) elaborated on the emotions categorised by Paul Ekman as:

Happiness: The muscles of the cheeks raise, eyes narrow, lines appear at the corner of the eyes, the corners of the mouth turn up.

Surprise: The eyebrows raise, there is a slight raising of upper eyelids and dropping of the lower jaw.

Sadness: The eyelids droop as the inner corners of the brows raise and (in extreme sorrow) draw together, and the corners of the lips pull down.

Anger: The eyebrows are pulled together and lowered, the lower eyelid is tensed, the eyes glare, and the lips tightened, appearing thinner.

Goman (2015) noted that whenever any of these emotions are felt strongly, their display is intense and can last up to four seconds. Micro expressions (facial displays lasting less than one-fifth of a second) can give an astute observer a glimpse into your true emotional state. Ekman and Friesen (2003) explain that Microexpressions are typically classified based on how an expression is modified. They exist in three groups:

Simulated expressions: when a microexpression is not accompanied by a genuine emotion. This is the most commonly studied form of microexpression because of its nature. It occurs when there is a brief flash of an expression, and then returns to a neutral state.

Neutralized expressions: when a genuine expression is suppressed and the face remains neutral. This type of micro-expression is not observable due to the successful suppression of it by a person.

Masked expressions: when a genuine expression is completely masked by a falsified expression. Masked expressions are microexpressions that are intended to be hidden, either subconsciously or consciously.

Goman (2015) explained that expressions that are not genuine can be identified by the following behaviours:

- An expression that does not use all the muscles in the face typically associated with that expression is usually fake.
- Because all genuine expressions (with the exception of contempt) are symmetrical, any display of other expressions that are asymmetrical, are suspect.
- An expression held for more than five seconds is typically not genuinely felt. Most real expressions last only for a few seconds.

Currently, only highly trained individuals are able to distinguish them, but even with proper training the recognition accuracy is only 47% (Wu et al.,2018). It is important to note that recognition accuracy varies among researcher schools. Consequently, Ekman (2003) noted that people who are highly trained in observing facial movement also tend to make somewhat accurate judgments when they see the videotapes of the subjects who lie or tell the truth about the emotions they felt. In a study Ekman (2003) showed the face-only videotapes to four associates who had been using a technique for measuring the face for more than a year. Each of these four people achieved an accuracy score of 80% or higher. Thus, the conclusion is that the face does contain accurate information, as well as misinformation, when people lie.

Subsequently, Goman (2015) recognised that It is difficult to hide your feelings because many emotional displays are almost impossible to eliminate. The Adam's-apple jump (especially noticeable in men) is one such emotional cue – an unconscious sign of emotional anxiety, embarrassment, or stress – often displayed when someone hears something he strongly dislikes or disagrees with. Even if the person is successful masking their emotions, an audience

will still know that something is “off.” Physiological measures based on remote Photoplethysmography (PPG) can give significant extra insights into micro-expressions which cannot be measured using facial expression analysis solely. PPG is a technique by which small changes in colour caused by the pulse of arterial blood passing through capillaries just under the skin’s epidermis is measured and used to determine the subject’s heart rate especially for subjects or situations where there is little variation in facial expressions, heart rate can be a useful additional indication of arousal. An increase in heart rate does not indicate if this is due to a positive (e.g. surprise) or negative (e.g. fear) emotion, but does help to assess its magnitude (Uyl and Thews, 2018). To contextualise, Gross and Levenson's (1993) undertook a study in which subjects watched a disgusting film while suppressing or not suppressing their expressions, suppression produced increased blinking. However, suppression also produced a decreased heart rate in participants and self-reports did not reflect that suppression had an effect on disgust experience. While it is unclear from Gross and Levenson's study whether suppression successfully diminishes the experience of emotions, it can be concluded from this research that expressive suppression does not completely inhibit all facial movements and expressions (e.g. blinking of the eyes).

Pfister et al., (2011) explained that the major challenges in recognising micro-expressions involve their very short duration and involuntariness. The short duration means only a very limited number of frames are available for analysis with a standard 25fps camera. To allow accurate recognition, a camera with high frame rate can be used or an alternative method needs to be developed. Furthermore, with large variations in facial expression appearance, a supervised machine learning approach based on a training corpus is expected to best suit the problem. Acted facial expression corpora are least challenging to gather. However, since micro-expressions are involuntary, acted micro-expressions will likely differ greatly from spontaneous ones. Gathering a comprehensive training corpus therefore requires considerable psychological insights and time-consuming experiments to successfully induce spontaneous micro-expressions. Deceptive behaviour is very subtle and varies across different people. Thus, detecting these subtle micro motion patterns, e.g. micro facial expression, itself is a challenging problem. In terms of advancements there have been algorithms developed to help spearhead research into detecting micro-expressions such as the Temporal Interpolation Model (TIM) (Pfister et al.,2011). In addition, Duran et al., (2013)

suggested that research should focus more on the movement dynamics and behaviour structure. Going by this assertion, this thesis also acknowledges that detecting micro-expressions is challenging and more emphasis should be placed on behavioural dynamics without detecting facial landmarks, then use behaviour dynamics to learn micro-expressions and deceptive behaviour. Furthermore, current facial expression suppression detection methods have improved from using human cues to technology using machine learning algorithms (Wu et al.,2018).

2.3.3 ROLE OF EMOTION IN DECISION MAKING

Barden (2018) made a reference to Damasio’s book “self-come to mind” which explores the role of emotions on decision making that describes memories as having ‘somatic markers’ – emotional “tags” that get ascribed to the mental representation of a situation, object, or place. The tags then act as a signal to the brain whenever it encounters or considers that thing and sets the scene for interpretation or consideration of other things we think or hear about it. Brands use this principle when trying to build positivity through their advertising. Even though people may not have directly experienced a brand for themselves, telling them good things about it and making them feel positive towards it can result in this positivity becoming associated with the brand itself, framing brand experience, and helping people experience the brand through rose tinted glasses. Hobbs et al., (2017) emphasised that the best way to measure how effective a video will be is to measure the emotional response to it – because the higher the engagement is, the more likely a viewer will take action. For example, a study done with Mars across 35 brands established a link between the emotional perception of an ad and its impact on sales with 75% certainty. It has also been established from prior studies that facial expressions induced from the cognitive state of emotional activity are key for making decisions through the concept of affect.

It is noted that an important aspect of social behaviour is facial expressions, as it contains valuable information that may influence an interaction. From the facial expression of an opponent, **one may infer not only emotional states but also information regarding intentions**, personality and complex social characteristics. For example, from a smiling expression of a participant watching a video stimulus in this thesis, intentions such as trust, cooperation, or affiliation might be inferred, therefore facilitating approach behaviour and a

higher intention to share the video. By contrast, an angry facial expression might be interpreted as threatening, spiteful, and associated with intentions such as rejection, which subsequently might facilitate avoidance behaviour or the intention to be less interested in viewing the video in full and subsequently sharing it. Based on this premise, it is expected that facial expressions have a direct influence on decision-making (Mussel, Goritz and Hewig, 2014). People's facial expressions, whether made consciously or subconsciously, continuously reveal their state of mind. To the extent that there is on-going research that proposes methods for predicting people's strategic decisions based on their facial expressions (Peled et al., 2014).

2.3.4 THE SCOPE OF MOOD

Having considered emotions another important variable that had to be taken into consideration within this study is the effect of mood on emotions when subjects are placed in a condition to view a video stimulus. Inherently, mood is defined as a consumer's affective state that is relatively global in nature, as opposed to emotions, which tend to have a specific cause (Gardner, 1985). Baggozi, Gopinath and Nyer (1999) posits that the line between emotions and moods is difficult to draw but often by convention involves conceiving of a mood as being longer lasting (from a few hours up to days) and lower in intensity than emotion and yet still another distinction is that emotions are intentional whereas moods are generally nonintentional. Within the field of mood research, a variety of moods are available for study. For example, in the context of negative moods, researchers have called attention to sad moods (Rusting and DeHart, 2000) and anxious moods (Thayer, Newman, and McClain, 1994). Kim and Mattila (2010) indicates that a substantial amount of research supports the notion that mood states influence judgments in a mood-congruent manner. Positive moods result in more favourable evaluations, whereas negative moods result in more negative evaluations. Compared to intense emotions, moods are milder, pervasive, and generalised affective states that are induced by various factors. Generally, moods are expressed as positive or negative without a specific target, and moods last for some duration. A person might watch a humorous viral video with prior mood states, which can be either positively or negatively valenced. Accordingly, mood states have important effects on customer behaviours (De Ruyter and Bloemer, 1999), one participant prior to the start of the study categorically gave a verbal cue and stated that she is "always happy" and hence, by her

admission , participation in the research could potentially skew the results regardless of the video content viewed , empirically it was observed that the “happiness” emotion elicited by the said participant during the test was higher than the mean average of the entire participants. Additionally, It is also evident on pg. 112 (i.e. comparing lab users versus remote users) that both positive mood and negative mood had an effect on the emotional variations. Having summarised the scope of emotions and the role that mood plays in effecting emotions the next stage is to assess how emotion effects “decision making” most importantly within the context of “the intention to share”.

2.4 VIRAL VIDEO PHENOMENON

The study of virality and diffusion cannot exclude the works and scholarly contributions of Jonah Berger whose works such as “arousal increases social transmission (Berger,2011), “What drives immediate and ongoing word of mouth ”(Berger and Schwartz, 2011) , “what makes online content viral (Berger and Milkman,2012)”,“contagious why things catch on (Berger,2013)”,“Word of mouth and interpersonal communication: A review and directions for future research (Berger,2014)”: has been cited and reviewed by other researchers in the viral marketing discipline. Berger (2011) acknowledged that recent work on the social sharing of emotion (Which is one of the main theoretical framework adopted in this study) suggests that positive emotion may also increase transmission, albeit why emotions drive sharing and why some emotions boost sharing more than others remains unclear with certain types of content being more viral than others. Since this research lays a huge emphasis on emotions per the theory of social sharing of emotions, Berger’s work is invaluable in underpinning this study. Which qualities of marketing messages are those that trigger the willingness in consumers to share them? If we observe most successful non-commercial viral videos, we can see that one of the connecting themes is risqué and humorous content. Companies, however, cannot afford to embed just any type of content in their advertising, with their brands reputation on the line. Eckler and Bolls (2011) approached this problem from the information processing perspective. Their goal was to understand how the valence of a marketing message affects the intent to forward it. In their study they use viral videos of varying emotional tonalities (pleasant, coactive and negative) and measure attitudes toward the ad and the brand and the consequent intent for forwarding. They find that pleasant emotional

tone elicits the strongest attitude toward the ad, attitude toward the brand, and intention to forward. The effects are weaker for coercive tone and weakest for negative emotional tone (Eckler and Bolls, 2011). The videos they used in this research are all commercial viral videos. Through their findings, they challenge the notion that risqué content is enough to make a message viral, at least when it comes to commercial virals. Positive tone plays an important role as well.

The study of Berger and Milkman (2012) corroborates these findings and builds further on them. In their study, they examine physiological reactions to online news articles content and the resulting intent to forward. They observe the sharing patterns of readers of New York Times articles. The articles used as stimuli are of different activation levels and different valence extremes (high-arousal positive, high-arousal negative, low-arousal positive and low-arousal negative). They find that positive content is always more viral than negative, thus validating the findings of Eckler and Bolls (2011). However, they point out that virality is not only a matter of valence. The more activating the content is, the higher the chance it will be forwarded. Thus, they demonstrate that the most viral type of content is that which is both positive and highly activating. The likelihood of negative content getting shared would increase with the level of activation the emotion elicits (going from sadness as lowly activating to anger as highly activating)

Furthermore, Berger and Milkman (2012) explained that one reason people may share stories, news, and information is because they contain **useful information**. Coupons or articles about good restaurants help people save money and eat better. Consumers may share such practically useful content for altruistic reasons (e.g., to help others) or for self-enhancement purposes (e.g., to appear knowledgeable). Practically useful content also has social exchange value and people may share it to generate reciprocity. Berger and Milkman (2012) theorised that the emotional aspects of content may also affect whether it is shared. According to Berger, the connecting strand among all these types of emotions and virality is the element of surprise. The emotion of surprise is generated when something is unexpected or mis expected, with surprise resulting in responses of amazement and astonishment (Ekman and Friesen, 1975). This is in line with the previously discussed findings of Berger and Milkman (2012), as the emotional element of surprise is in fact a high level of activation emotion of either valence, positive or negative. Based on the findings presented so far, the safest bet for

video marketers attempting to create a viral campaign would be to make a high-arousal, positive piece, evoking the feeling of joy and containing an element of surprise. However, that also probably describes a large portion of advertising published daily, most of which does not become viral.

2.4.1 NEGATING FACTORS IN VIRALITY

The sharing of how we feel, or our emotions is rooted in the theory of social sharing of emotions (Berger,2011; Rime et al.,1991) which is ingrained in Psychology. By applying the theoretical framework, Berger undertook a related experiment to understand diffusion using psychological approaches both within theory and methodology. In order to explain how virality is rooted in Psychology Berger primarily used the psychological aspects of **arousal** and **emotions** in his research works (i.e Berger,2011; Berger and Milkman,2012). In order to distinguish the two, Heilman (1997) explains that the term arousal, like the terms attention and emotion has several physiologic definitions. Where one of the key definitions usually refers to the excitatory state of neurons or the propensity of neurons to discharge when appropriately activated. Emotional arousal is consequently seen as an essential component of such experiences as pleasure and displeasure, sadness and happiness, love and hate, despair and elation, gaiety and dejection, rage and exultation, exhilaration and grief, frustration and triumph, merriment and fear, anger and joy, and so on. Features common to all acute emotions are that their high arousal intensity is comparatively short-lived and that they show a strong focus on both causal circumstances and motivational implication. Berger's view on the universality of emotions appears to be consistent with that of Paul Ekman where everyone elicits the same kind of emotions when exposed to similar stimuli , with the arguments set against that notion been explicitly spelled out by critics of Ekman, the distinction being that some emotions are positive and other's negative , Berger, apparently preferred to classify emotions on a second dimension , which is that of activation , or physiological arousal where the emphasis is to focus on feelings , the underlying emotions that motivate people to action (Berger, 2013).

Another key reproach against Berger is that he does not state if there might be any other variables responsible for viral content with authors such as Bampo et al.,(2008) citing the social structure of digital networks. It is also important within the context of this research to

note that emotions and the state of arousal are inextricably linked. Emotions and arousal are thus, the core of the psychological aspects within Berger's work with varying definitions and debates as to what actually constitutes emotions. However, within the context of emotions, the autonomic response to unexpected stimuli (e.g. doors slamming, spiders, roller coaster rides, snakes etc), which involves an increased heart rate, sweaty palms, and irregular or faster breathing readies us for action. In response to perceived threats, our body readies us for flight from, or fighting with, the perceived threat (Evans, 2001).

A theory of individual feelings can provide names, valence, level of arousal, the cause, expression, whether it was culture specific or innate, basic or higher cognitive, the signal and action and the individual physiological markers. Unfortunately, research tends to focus on basic emotions such as fear, anger and sadness rather than all possible emotions (Ekman, 1994). This may be an outcome of the lack of agreement of what basic emotions are. Specific words used to describe feelings often differ in different cultures, differ across time and even in different social groups within a culture. 'Happy' can also be referred to as 'joyful'. The nuances of 'feeling words' highlight how difficult they are to qualify. While agreement on feelings is not unanimous it seems clear that there are several basic emotions with many derivatives.

The use of Psychological or Neuroscience methods have been used to understand the diffusion of information. Berger (2013) cited Harvard neuroscientists Jason Mitchell and Diana Tamir who found out that disclosing information about self is intrinsically rewarding. In one study, the researchers hooked up subjects to brain scanners and asked them to share their own opinions or attitudes ("I like snowboarding") or the opinions or attitudes of another person ("He likes puppies"). They found out that sharing personal opinions activated the same brain circuits that respond to rewards like food and money. In relation to Berger's own research Berger first hypothesised that social transmission is driven in part by arousal (Berger, 2011). This notion was tested in two experiments. The first experiment which is more pertinent to the study examined how manipulations that increase general arousal (i.e., watching emotional videos or jogging in place) affect the social transmission of unrelated content. In the first experiment, 93 students completed what they were told were two unrelated studies. The first evoked specific emotions by using film clips validated in prior research. Participants in the control condition watched a neutral clip; those in the

experimental conditions watched an emotional clip. Emotional arousal and valence were manipulated independently so that high- and low-arousal emotions of both a positive (amusement vs. contentment) and a negative (anxiety vs. sadness) nature were evoked in different conditions. Participants rated how aroused they felt after watching the video, using three 7-point scales (passive–active, mellow–fired up, and low–high energy). In what participants were told was the second study, social transmission was measured. Participants were shown an article and a video, both pretested to be emotionally neutral, and rated how willing they would be to share each with friends, family members, and co-workers, using a scale ranging from 1 (not at all) to 7 (extremely). An ANOVA analysis on the data have shown that participants induced to feel amusement or anxiety (high arousal) were more willing to share content with other people, $F(1, 71) = 6.65, p < .05$. In addition, comparing each experimental condition with the control condition indicated that emotions characterized by high arousal boosted transmission, $t(89) = 2.30, p = .02$, for anxiety and $t(89) = 1.72, p = .09$, for amusement (note: it appears there is a logical error as the p -value is greater than the α).

Similarly, in a related study using a unique dataset of all the New York Times articles published over a three months period, the authors (Berger and other researchers) examined how emotions shaped virality. The study first examined how content's valence (i.e., whether an article is positive or negative) and the specific emotions it evokes (e.g., anger, sadness, awe) affect whether it is highly shared. Secondly, the researchers manipulated the specific emotion evoked by content to directly test the causal impact of arousal on social transmission. To undertake the experiments a variety of methods used in Psychology were applied, article coding (these were a combination of sentiment analysis to quantify the positivity and emotionality of each article, automated rating using a software (LIWC) and likert scale. The findings indicated that positive content is more viral than negative content, but the relationship between emotion and social transmission is more complex than valence alone. The other experiment also supported theory from the work done prior to suggest that virality is partially driven by physiological arousal. Content that evokes high-arousal positive (awe) or negative (anger or anxiety) emotions is more viral. Content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral. These results hold even when the authors control for how surprising, interesting, or practically useful content is (all of which are

positively linked to virality), as well as external drivers of attention (e.g., how prominently content was featured). The experimental results further demonstrated the causal impact of specific emotion on transmission and illustrate that it is driven by the level of activation induced. Within the context of this study and the justification for the methodology It is important to state that Berger's research methods did not incorporate the use of the facial expression analysis or the Galvanic Skin Response (GSR) it does not in any way limit the notion that there exists minimal link between facial expressions and emotions or arousal, Berger, rather emphasises that the sharing is as a result of arousal activation and rather considered methods that were in line with the research design.

2.4.2 PREDICTING VIRALITY

One of the biggest hurdles video marketing managers have is how to create a viral video to get the word out. There has been contemporary ongoing research into factors that drive video virality with researchers pointing out emotions, social networking ties and content as being some of the most prominent. As discussed in the previous chapters understanding what factors contribute to virality is essential but harnessing a range of models that explain and predict virality is more advantageous. There have been some models created and tested which purport to predict virality using interactive visualisation systems which rely on the metadata of YouTube videos and statistical algorithms to extrapolate the traction a video will have over time. This chapter aims to discuss the current existing models that intend to predict the virality of videos. Some existing models tend to place emphasis on historical YouTube metadata or sharing behaviours which is then extrapolated using statistical algorithms to predict the traction of views of a video over time (Crane and Sornette, 2008; Kong et al.,2018) , the argument is that without any concrete historical data such as the number of views or shares it will be very difficult from the onset to predict if the video will go viral. However, there are other models that tend to use existing emotional data generated to predict the virality of videos in real time (Elis et al.,2014; Jiang, Xu and Xue,2014; Jou, Bhattacharya and Chang, 2014) . Whatever approach that is taken a gap that exists in the market is potentially solved. The gap concerns video marketers who need to choose which videos to promote by identifying potentially viral videos. But in order to choose what model or method to adopt it

is important to understand the intrinsic make of the models which will also position this research into the exact model it chose to uniquely develop for the prediction of viral videos.

Some historical methods worthy of mention include the HIPie that is a tool that uses a model which explains online virality by linking exogenous inputs from public social media platforms, such as Twitter or Youtube, to endogenous responses within the Youtube content platform, which account for the word-of-mouth process occurring around videos. HIPie differs from other works in several ways. First, it aims to be more than a demonstration of a scientific algorithm: it is a visualization platform dedicated to users. It has multiple visualization components and the user-friendly interaction enables this platform to easily convey the modeling outcome. Second, this platform is built for Youtube video virality modeling, while other platforms generally deal with Twitter, news article etc (Kong et al.,2018). Another model worth depicting is the CMU model which looks at the datasets of viral videos to forecast the peak day of the videos in future using endogenous variables. This video takes a video as input, and outputs the estimated number of days left before the viral video reaches its peak views. The proposed method takes into account a video's title and text description , the category, duration, upload time , title length, description length , the accumulated view count, likes, dislikes and comments up the current time (Jiang et al.,2014).

As discussed prior some real time predictive models that need to be taken into account which uses real time approaches for predicting emotions based on video content analysis include the mid-level concept feature and computational approaches which rely on complex data segmentation and extraction models (Elis et al.,2014; Jiang, Xu and Xue,2014; Jou, Bhattacharya and Chang, 2014). The main distinction between these real time models and the one used in this thesis is the mode of emotional measurement (i.e FaceReader) and the theoretical application which is based on the distribution bell curve which gives its own unique identity.

This chapter gave a very definitive overview of the diverse predictive models that researchers can use into predicting virality. Research is still on-going into exploring other models, and the onus is on the researcher to evaluate whether the model adopted uses real time or historical data whilst evaluating both the pros and cons to determine the extent a video stimuli would go viral.

2.5 CONCEPTUAL FRAMEWORK

After people have experienced an emotional response to content, they consider the option of passing the content on to their social networks (Feder, 2014). The **Social Sharing of Emotion theory** explains why people aim to connect with others after emotional experiences, and how this sharing of emotional content, in turn, causes emotional reactions in others - which can be termed as an intrinsic sharing trigger (Christophe and Rime, 1997). Rime et al. (1992) explored the phenomenon as to whether people share their emotions, whether they do it more readily than others, how often and with whom they speak about such experiences. **The findings showed that most emotional experiences are shared with others shortly after they have occurred, and that social sharing of emotions represents an integral part of emotional experiences.** Wagner et al. (2014) supported the stance to explain that one of the most fundamental characteristics of human beings is their social nature where there is a need to form social bonds to share experiences. By socially sharing their experiences individuals can modify their subjective perceptions of these experiences in a positive manner. Wagner et al. (2014) illustrated that when people go to the cinema, they rarely do so alone but in most cases go together with a partner or a friend. Apart from expecting to be emotionally moved by the film itself, they anticipate a positive impact of sharing this emotional experience with a peer, even though both are passively watching an event and there are only minimal opportunities to talk to each other during the viewing.

The conceptual framework below further depicts that shared emotional experiences can be influenced by positive and negative emotions. It can be hypothesised from the preceding literature that the intensity of the emotional elements of happiness and surprise are a predictor to the extent a video goes viral. Therefore, a video that elicits a high level of surprise or happiness will achieve virality as opposed to a video that exhibits a high level of anger, sadness or disgust. The conceptual framework also hypothesises that Fan groups (Football fans and Non-football fans) and other demographics (i.e Age and gender) determines the relationship strength between a viral emotions and intention to share, thus being the moderating variable. This is supported with current studies that focused on interpersonal factors that contribute to the spread of content online and has looked at the social network component of viral marketing. More specifically, it refers to research that

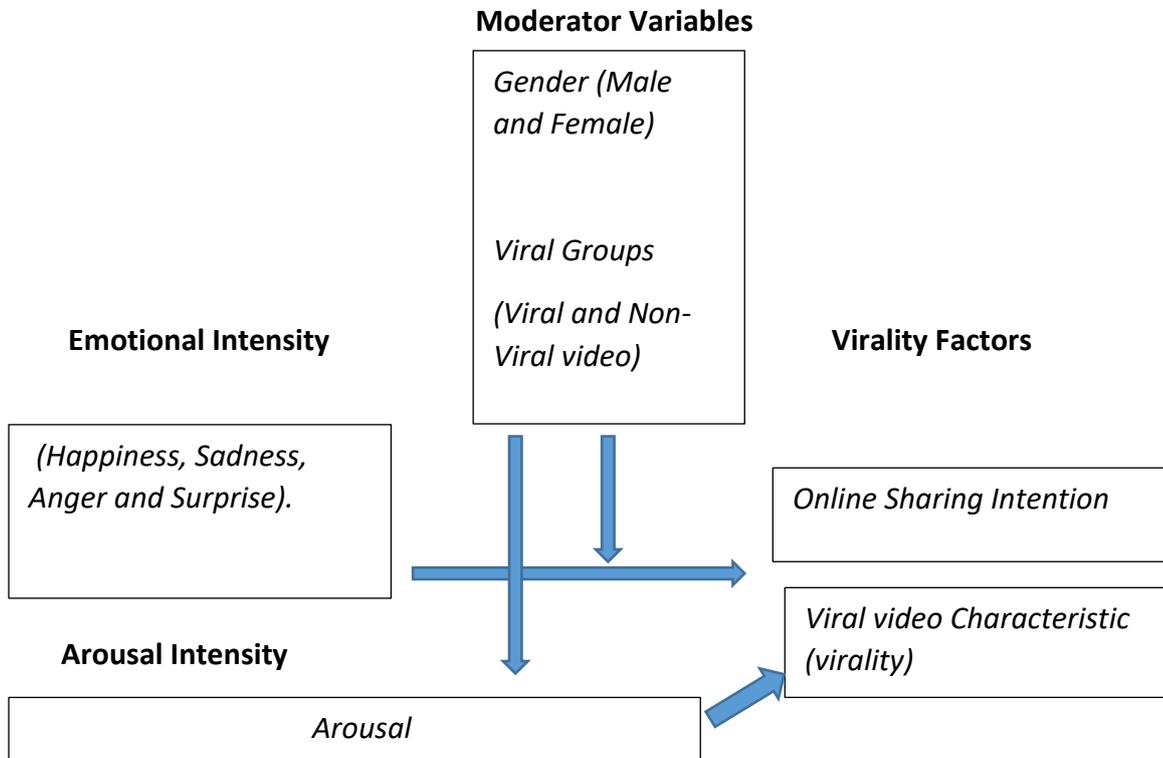
looked at social and community-oriented justifications as reasons why content gets spread online.

Social justifications for the spread of viral messages suggest that passing along content online builds social networks and social capital, it is important for society, and people anticipate that others would feel happy and grateful to them for sharing viral content (Izawa, 2010). Ho and Dempsey (2010) for example found that internet users' motivation to share content online, forms part of their need to be part of a group. Hence, the hypothesis is that Football fans will share amusing football content to their fellow football fans perpetually. An aspect of **Social Identity** is Social validation which is the tendency for individuals to look to others to see what others are doing to determine if a behaviour is normative and appropriate (Guadagno et al., 2013). In environments where the correct course of action is ambiguous, people rely even more heavily on the cues provided by others. People are also more likely to follow the cues of others when the others are a member of their in-group and thus more like them. Thus, in terms of Internet videos, when one receives a forward from an in-group member, that may serve as a signal that the video is appropriate to forward to others. To contextualise a Salford City Football fan will attend either home and away games of the team, buy the clubs paraphernalia and merchandise, watch and share football video highlights on YouTube with Salford City football fans who have a strong inclination to associate with the ideals and do likewise.

From the **theory of planned behaviour**, it is debated that intentions are equally as important as actual actions, since in most cases they are a strong predictor of future outcomes (Mikalef, Giannakos and Pateli, 2013). As evident in the conceptual model the intention to share was the prime construct developed based on this theory. The intention to share was influenced by numerous factors and contingencies, such as emotion intensity, age, gender and fan groups. Online intention to share was measured using a statement that address a participant's intention to share a video content. **Participants used a 5- Likert scale to respond to the specific statement. The intention to share statement was: "How likely will you be to share this online video with friends, family members or co-workers"?** General online to share intention scores was calculated for each participant by taking the average of the participant's responses. Because the statement used in the survey for this study is like the one used

previously by other researchers, i.e. Berger (2011) it can be said to have face and content validity.

Figure 11 Conceptual Framework



2.5.1 HYPOTHESIS

A conceptual model was designed to study the effects of online video sharing intention and virality. The relationships between the predictors (independent variables, dependent variables and moderating variables) will be analysed in the hypothesis below.

VARIATION IN EMOTIONALITY AND AROUSAL ON VIDEO GROUPS

H1: There is a significant difference in happiness (positive emotion) among fan groups who watch a viral video and a non-viral video.

The hypothesis aims to support existing research where happiness (i.e. positive emotion) is most dominant in viral videos (Dobele et al., 2007; Berger and Milkman, 2012; Nelson -Field, Riebe and Newstead, 2013).

H2: There is a significant difference in surprise (neutral emotion) among fan groups who watch a viral video and a non-viral video.

The hypothesis aims to support existing research that stipulates that content that includes an element of surprise is key to diffusion (Dobele et al.,2007).

H3: There is a significant difference in anger (negative emotions) among fan groups who watch a viral video and a non-viral video.

Berger and Milkman (2012) explains that anger might increase transmission (because it is characterized by high arousal, which triggers a desire to act by states of heightened activation and outward action.

H4: There is a significant difference in sadness (negative emotion) among fans groups who watch a viral video and a non-viral video.

Berger and Milkman (2012) classified sadness as a negative emotion where sadness is characterized by low arousal or deactivation. Berger and Milkman (2012) explains further that sadness might have no effect or even decrease transmission (because it is characterized by low arousal).

H5: There is a significant difference in arousal intensity among fan groups who watch a viral video and a non-viral video.

Nelson – Field, Reibe and Newstead (2013) concluded from the studies that low arousal content is negatively linked to virality. Berger and Milkman (2012) argue that high arousal activation is positively linked with virality.

ONLINE INTENTION TO SHARE.

H7a: Happiness (positive emotion) is positively associated with the intention to share a viral among football fans.

The aim of the hypothesis is to directly test the strength of the relationship between happiness and the intention to share online by football fans. It has been hypothesised from preceding literature that content that evokes activating emotions (i.e. happiness) is more likely to be shared, by manipulating specific emotions such as happiness in a controlled setting.

H7b: Happiness (positive emotion) is negatively associated with the intention to share a viral video among non - football fans. The hypothesis posits that non-football fans will be less willing to share despite eliciting happiness.

H8a: Surprise (neutral emotion) is positively associated with the intention to share a viral among football fans.

Berger and Milkman (2012) noted that participants induced to feel amusement or surprise (high arousal) are more willing to share content with other people. The hypothesis posits that football fans will be more willing to share when amused.

H8b: Surprise (neutral emotion) is negatively associated with the intention to share a viral video among non - football fans. The hypothesis posits that non-football fans will be less willing to share despite eliciting surprise.

H9a: Anger is positively associated with the intention to share a viral among football fans.

Berger and Milkman (2012) explained that content is more likely to be shared when it is induced by anger which is based on the arousal it evoked. The hypothesis posits that football fans will be more willing to share when amused.

H9b: Anger is negatively associated with the intention to share a viral among non- football fans. The hypothesis posits that non-football fans will be less willing to share despite eliciting anger.

H10a: Sadness is negatively associated with the intention to share a viral video among football fans.

Berger and Milkman (2012) explained that content that evokes more sadness, should be less likely to be shared because it deactivates rather than activates. Hence, the hypothesis posits that football fans will be less willing to share when sadness is elicited.

H10b: Sadness is negatively associated with the intention to share a viral video among non-football fans. The hypothesis posits that non - football fans will be more less willing to share.

H11a: disgust (positive emotion) is positively associated with the intention to share a viral video among football fans.

The hypothesis posits that football fans will be less willing to share when disgust is elicited.

H11b: disgust is negatively associated with the intention to share a viral video among non - football fans.

The hypothesis posits that non - football fans will be more less willing to share when disgust is elicited.

2.6 SUMMARY

This chapter provided a framework which was obtained from a synthesis of the Social Sharing of Emotions Theory (SSET), Social Identity Theory (SIT) and some aspects from the Theory of Planned Behaviour (TPB) in addition to components from other literary sources. This chapter further highlighted the need for further research into viral marketing, with emotions and social groups being a key area for extended studies. The literature review showed that emotions , arousal and mood plays a significant role in the diffusion of viral videos. The chapter evaluated the relevant literature on facial expressions which is intertwined with emotions to understand the propensity to share a viral video.

The literature review was instrumental in providing a taxonomy of the diverse kinds of emotions such as “mock expressions” and “fake emotions” which critics will argue as it being fundamental to whether their emotions are “real” enough to help instigate a social contagion. The literature on video virality was split with the first part looking at the psychological aspect that underlines sharing and the second part focused more on the viral video phenomenon as it pertains to marketing with emphasis on the work from Jonah Berger. It was noted that emotions and arousal are fundamental to this study in addition to specific groups where in the context of this thesis the dynamic (“in group – football fans”) and (“out group” – non football fans) is fundamental. The literature review underpinned this study with respect to exploring emotions and arousal, with a further outlook on researching to what extent emotions and what specific emotions are important for a video to go viral , secondly it raised the aspect of whether virality can be predicted and the methods for measuring video virality by other researchers. The theories used surveyed the role of the individual’s attitudes towards sharing video content as well as the subjective norms in determining viral behaviour. The framework is used in this thesis to examine the intrinsic sharing triggers and the intention to share videos online. Demographic factors of the online sharers are focused on variables

such as fan groups, gender and age. They are all indicators that determine the extent people will share content online. Finally, some of the criticisms of emotions and virality as a concept as a unified theory were raised. This thesis aimed to acknowledge these criticisms, albeit an depth defence of social sharing of emotions theory , social identity and theory of planned behaviour as a unified concept was not the aim of this thesis.

3.0 METHODOLOGY

The previous chapter established the need for a framework that captures the factors affecting the online sharing of video content. The chapter aims to present and discuss the research methodology adopted for achieving the research objectives. The chapter starts by explaining the three types of paradigms considered for this study: the critical social science paradigm, the interpretive and positivist. In addition, the assumptions underlying the three paradigms are presented and discussed. The justification is made for the use of the positivist approach for this research. Additionally, the types of research such as exploratory, descriptive and explanatory will be discussed and the choice of descriptive study justified. Consequently, the chapter discusses the research design and implementation of quantitative research using facial expression analysis and the embedded web questionnaire as data collection tools. The chapter then provides a detailed explanation of the sampling issues encountered, the steps undertaken to conduct both the facial expression analysis and web-questionnaire, and how the data from the two methods was subsequently prepared for analysis.

3.1 PHILOSOPHICAL PARADIGM

An appropriate research paradigm correlates through the comprehension of the research philosophy, which defines a pertinent aspect in relation to the way research is conducted. Easterby-Smith et al. (2008) suggest that the creation of an understanding about research philosophy requires provision of clarification of research designs. It is, therefore, paramount to identify and select the most suitable philosophy at the inception of the research process as it provides solid ground for the study (Coghlan and Brannick, 2014). According to Pittaway (2006), paradigms identify the development and enhancement of the scientific practice in relation to the developed philosophies and assumptions pertaining to the world, together with the nature of knowledge. Paradigms, therefore, identify the way research is carried out. The assumptions developed include ontological and epistemological assumptions. Ontological assumptions refer to a branch of meta-physics, which identify an element of philosophy that seeks to assess the nature of existence (Pittaway, 2006). Ontological assumptions place emphasis on the nature of reality and develop an understanding on the construction and representation of reality within the human conscious (Pittaway, 2006).

Epistemological assumptions stand for a branch of philosophy that studies the nature of knowledge through identifying its source forms. Epistemological assumptions study the process in which individuals create an understanding together with a conceptualization related to the world around them through development of assumptions pertaining to the aspects that constitute knowledge, together with identification of its consequent construction and communication (Saunders, Thornhill and Lewis,2009). Identification of the most suitable philosophy remains dependent on the association developed between the philosophy and the research questions of the thesis. Kura (2012) outlines three pertinent philosophies utilized in modern research. These three paradigms are: Positivism, Interpretivism and Critical Social Science. Furthermore, Bryman (2012) stipulates that all philosophical approaches provide both positive and negative impacts in various research contexts. The following sub-sections will explore the three options considered for this study and justifies the selection made based on **Epistemology, Ontology, Axiology and Methodological** constructs.

3.1.1 CRITICAL RESEARCH

A key approach within social sciences which includes the fact of multiple level of reality, is critical paradigm. The research aim from this perspective is not to study the social world but to change it” (Neuman, 2011). Conducting research in a critical manner entails actionable research on the topic (Bhattacharjee, 2012), if a complex phenomenon of social research is perhaps more appropriately tested by making observations on how the actions affect the population at the individual level. The corresponding ethnography is directed towards building the necessary theory which employs an inductive approach relating to the data involved. This paradigm has its own origins in critical theory.

Epistemology

Critical research is unique in the sense that knowledge is not viewed as discovered through objective inquiry but as acquired by way of critical discourse and debate. It concentrates on the critique of, and revolution in, current structures, conditions and relationships that prevent the development of social practices in organisations and communities through investigating them in their historical, cultural, social and political contexts (Pope and Mays, 2008). Similarly,

inquiry is not directed at acquiring knowledge for its own sake; rather, it employs understanding as a tool to be used to contribute to the on-going process of practical change in the social world. Therefore, the methodologies in this research paradigm should aim to foster mutual learning, self-reflection, participation and empowerment, instead of the mere acceptance of discoveries (Wadsworth and Epstein, 1998).

Ontology

Critical social theory makes two major assumptions (Creswell, 2013). It disagrees with historical ontology which states that there exists a reality created and shaped by social, political, economic, cultural, gender-based and ethnic forces that have been crystallised over time into the societal structures, and is, therefore, taken to be 'real' or natural. Critical researchers maintain that they should not function under the assumption that these structures are real, as what is important is the method of accurately knowing the reality. Furthermore, critical social theory supports modified transactional or subjectivist epistemology which claims that one cannot separate oneself from what one knows, and this stands in the way of inquiry (Williams, 2014). What is there to be known is intimately linked to the interaction between the investigator and the object and group. In other words, this theory is oriented towards critiquing and changing society, as opposed to traditional theories which seek to understand and explain it.

Axiology

Furthermore, they state that the goal of research should be to bring about change by actively challenging interpretations and values. Others argue that this is inevitable, since politics, inquiry and change are inseparable, and through an agenda of development, all contributors' lives can be changed for the better (Creswell, 2013). Hence, this approach is often referred to as the transformative paradigm.

Methodology

Research conducted within the critical social science paradigm adopts a methodology that tends to combine dialogic methods; that is, methods involving both observation and interviewing, and making sure that the approaches encourage conversation and reflection. It gives the researcher and participants a chance to question the 'natural' way of things and challenge the mechanism of maintaining order. Therefore, instead of naming or describing a

situation from a certain point of view or a set of values, the critical researcher attempts to question and challenge the guiding assumptions traditionally held by the people in that particular society, and hence come up with ways of changing the situation for the better. As a result, such research will begin with an assumption of what is perceived as good, ideal or desirable, for example, democracy or autonomy, and then proceed to ask the people in a social setting, such as a culture, group or organisation, to reflect on and assess their current situation with reference to the identified values. For example, a researcher may ask participants, 'To what extent are you a democratic republic?' This can then be analysed on a scale to know how far the current case is from the ideal and what can be done to reach a desirable level. To sum up, the critical social science paradigm consists of research undertaken to uncover hidden truths that account for social relations and empower people to change their social world (Creswell, 2013). Human beings are viewed as creative, adaptive creatures, who are full of untapped potential, trapped by the social forces that exploit them. Moreover, in this paradigm, the social reality is considered an important resource that can help people understand their own experiences and consequently improve their conditions or social environment. There exist several differences between the three research paradigms and choosing the appropriate one depends on the research topic, objectives and questions.

3.1.2 INTERPRETIVISM

A large body of research in social science is based on interpretive approach as well as positivism. Interpretive research concerns how people interact with each other. In general, this approach is defined as "the systematic analysis of socially meaningful action through the direct detailed observation of people in natural settings in order to arrive at understandings and interpretations of how people create and maintain their social worlds" (Neuman, 2003, p.77) . Oates (2006) argues that interpretive studies do not prove or disprove a hypothesis, as in a positivist research which would be explained in the next segment but try to identify, explore and explain how all the factors in a particular social setting are related and interdependent.

Epistemology

The interpretivism philosophy stipulates that the researcher on effect the research (Saunders, Thornhill and Lewis,2009). This provides a challenge as the researcher enters into a new social world pertaining to study subjects and they have to develop an understanding and interpretation of the occurring phenomenon from the subject's social point of view (Pittaway, 2006). The interpretivism perspective is identified as highly applicable within business and management research as it is the base of research in various business fields including organizational behaviour, marketing and human resource management (Goulding, 2002). In fact, business situations are complex and unique within each setting as they require a function of a unique blend of situations and individuals who unite at various times (Saunders, Thornhill and Lewis, 2009).

Ontology

From an ontological perspective, interpretive researchers are incapable of understanding the existence of a reality that exists irrespective of people. Nonetheless, Mutch (2005) claims that reality is reflected in human conduct. Interpretive researchers utilize qualitative research methodologies to carry out investigation, interpretation and description of social realities.

Axiology

From an etymological perspective, the interpretivism view the patterns found in reality as developed from evolution, identifying incorporation of systems developed by people as they socially interact (Neuman, 2003). Interpretive researchers place more emphasis on the development of a better understanding of the world through the provision of primary experience and factual reporting, together with quotations related to the researcher's perspectives (Bryman, 2012). Interpretive researchers utilise data gathering methods sensitive to the context which enhances provision of a detailed description of social phenomena via providing participants with encouragement to enhance free speech. (Neuman, 2003). This necessitates understanding of the investigator's quest for insight in relation to the phenomenon experienced by the participants. Consequently, the most utilized form of data gathering tools are shown to be interviews, focus group discussions and naturalistic observation (Eysenbach and Kohler, 2002).

Methodology

In contrast to positivism, interpretivism does not define reality as independent from the human view. The interpretivism model describes individual experiences as different realities, identifying the possible existence of more than one reality. This suggests that it is impossible to create generalizations, as it would limit the significance of the phenomena. Denzin and Lincoln (2008) argue that the interpretive perspective is interrelated to qualitative methods as it allows flexibility of inquiry as opposed to stipulation of questions.

3.1.3 POSITIVISM

The word positivism is derived from the Latin word 'positum', which means the supine version of 'pono' or place. Therefore, positivism stands for something that is placed aside that provides facts utilized by the researcher. Data represents an element in existence and the researcher's task is gathering and systemizing the data (Alevesson and Skoldberg, 2009). According to Tobin and Joseph (2006), positivism is defined as a scientific method utilized in the conduction of research. This philosophy incorporates realism as an element capable of expression from an objective standpoint.

Epistemology

Further, the realist objectivist empiricist epistemology identified within the positivist model incorporate a research methodology that enhances objectivity and detachment, as it places immense emphasis on the measurement of the variables and testing hypotheses that are linked to general causal explanations. Ontology Positivism is based on the foundationalism of ontology (Cheal, 2012). A positivist views the world's existence as being independent of the knowledge learnt. Positivism, natural science and social science are highly similar.

Axiology

The positivist view assumes that the results about human behaviour can be generalized from the sample to the overall population (Mertens, 2009). Oats (2006) explains that positivism explores human behaviour in a similar way as incorporated within social science research. Moreover, Easterby-Smith et al., (2008) conclude that positivism necessitates accumulation of large amounts of data together, within the provision of a detailed theoretical focus. Subsequently, as theories incorporate more numeric measures pertaining to observations,

positivism enhances its standardized levels leading to replication of the studies, leading to increased testing and verification which increases the levels of reliability attached to the theory.

Methodology

The positivist research model tends to adopt the quantitative research methodology (Bryman, 2012).

3.3.4 THE CHOICE OF APPROPRIATE PARADIGM

The current research is conducted using a **positivist approach** which contributes to an enhanced understanding of the association between factors related to emotions and the corresponding factors affecting online video virality. As stated previously, Bryman (2012) has identified and listed the three main research paradigms under the headings of positivist, interpretive and critical research avenues. Furthermore, **Triangulation** which is necessitated in this study refers to the investigation of a phenomenon from at least two different perspectives (Preece, Rogers, and Sharp, 2011). Triangulation can be explained in the following contexts (Oates,2006):

- Triangulation of data means that data is drawn from different sources at different times, in different places, or from different people.
- Investigator triangulation occurs when different researchers (observers, interviewers, etc.) have been used to collect and interpret data.
- Triangulation of theories means the use of different theoretical frameworks in which to view the data or findings.

The current study will make use of triangulation of theories in which **the Jonah Berger theory, Social Sharing of emotions, the theory of Planned behaviour, and the theory of social identity** will be triangulated to encapsulate a total picture. Where appropriate, the methods used (i.e. Facial Expression Analysis and Online Web Questionnaire) will be triangulated.

The table below shows a detailed summary of the objective-subjective debate relating to the positivist paradigms, interpretivism paradigms, between critical social sciences and the current study, which draws upon theories by Oats (2006) and Bryman (2012).

TABLE 2 Philosophical Paradigm

Assumption	Critical Social Science	Intepretivist	Positivist	My research approach
Epistemology (Knowledge)	Knowledge is based on historical practice and no predefined measurements can conclusively prove or disprove a theory.	Subjective meanings and social phenomena.	Only observable phenomena can provide credible data and facts,	The current study will explore a phenomenon which is related to the sharing of video content online to instigate virality. The phenomenon explored can be analysed without the intervention of the researcher and can provide credible data and objective facts that can be interpreted in an objective way.

<p>Ontology (Nature of reality)</p>	<p>Reality is produced and reproduced by human beings</p>	<p>Reality and meaning making as socially constructed, subjective, may change, multiple</p>	<p>Objectivism, external, objective and independent of social actors</p>	<p>The current study approaches the phenomenon of online video virality in an objective way. This means that the views and the beliefs of the researcher has nothing to do the stages of the study of the phenomenon.</p>
<p>Axiology (role of values)</p>	<p>Researcher considers the process of change to be a predominant factor in the lives of others</p>	<p>Researcher is biased by worldviews, cultural experiences and upbringing. These will impact on the research</p>	<p>Research is undertaken in a value-free way</p>	<p>In the current study, there is not any factor that influences the study and its results except the phenomenon itself and the figures and statistics it yields. No social or cultural element affects the procedures and the conclusions and findings of the current study.</p>

Methodological (Research strategies)	Research practice and may examine the way others become educated	Qualitative approach	Quantitative approach	The current study is quantitative in the sense that it adopts a quantitative method to collect data and then figures and statistical information are used to understand the phenomenon.
--	---	-------------------------	--------------------------	--

Sources: (Kidd and Kral, 2005; Oats 2006; Bryman ,2012).

3.3.5 THE NATURE OF THE RESEARCH

Evans et al. (2009) believe that the purpose of a research initiative could be classified into three facets: explanatory, descriptive and exploratory. An explanatory study enables a better understanding of the issues related to aspects of the efficacy of the subject matter under consideration. Correspondingly, this is perhaps more related to the 'how' and the 'why', utilising multiple tools like case studies and histories, or related experiments for explaining the topic under consideration. Oates (2006) explains further that an explanatory study goes further than a descriptive study in trying to explain why events happened as they did, or outcomes occurred. The case study analysis seeks to identify the multiple, often interlinked factors that had an effect or compares what was found in the case to theories from literature in order to see how one theory matches the case better than others. The thesis is explanatory in the part where it aims to develop a model for instigating a viral online video campaign or explaining how it occurs from a synthesis of theories and literature.

Evans et al., (2009) explain how a descriptive study provides for a more realistic representation of the situation under consideration, since this is related to explaining and stating the observed situation and behaviour concluded from the study. Alternately, a descriptive study contributes to laying the foundation based on which an exploratory

research will be concluded. In this regard, it certainly helps in understanding the issue under consideration, with the initiative undertaken for identifying the specifics of the related variables in the study (Sekaran, 2000). Oates (2006) notes that a descriptive study leads to a rich detailed analysis of a phenomenon and its context. The analysis usually tells a story, including discussion of what has occurred and how different people perceive what occurred. Additionally, it has also been concluded that it makes sense to allow the incorporation of the descriptive research paradigms within the initial stages of the thesis since this provides input on aspects related to the how, where, when, what and who of the topic. Descriptive research is also associated with statistical methodologies in terms of the explanation and documentation of information which is related to the topic. This thesis is descriptive in some respects which relate to developing a metric for measuring virality, understanding which emotions are responsible for instigating online video virality and finding an effective method for measuring users' emotions when watching a video stimulus.

Hence, Evans et al. (2009) recommend that an exploratory research is conducted when the topic under consideration has not been evaluated in previous studies, with the primary objective of the process in the study being to gather as much basic information and data as possible towards supporting subsequent studies. Saunders , Thornhill and Lewis. (2009) claim that exploratory research provides a good platform to study and evaluate a new topic, especially if one is unaware of all the parameters involved regarding the subject matter. If the current study is exploratory, there would be multitudes of data involved which would be needed to be processed towards understanding the topic. There are also certain aspects of this research that can be considered intrinsically exploratory such as the use of emotional shift patterns to predict viral behaviour which is unique and needs further investigation. Oates (2006) explicated that a case study approach, whether exploratory, descriptive or explanatory can use single or multiple cases. If a multiple case study is adopted, each case is written up separately, but the researcher looks for similarities or differences between the different cases.

3.4 RESEARCH APPROACH

A research approach is the formulated plan and the procedure for investigation that span the steps from broad assumptions to detailed methods of data collection, analysis, and interpretation. However, it is split into two main investigative areas of quantitative and qualitative approach (Rasooli, 2006).

3.4.1 QUALITATIVE APPROACH

According to Rasooli (2006), the qualitative approach is identified by the proximity to the object of research. It seeks to incorporate knowledge aimed at enhancing investigative, interpretive understanding of the phenomena through provision of an inside perspective (Yin, 2003). The nature of qualitative data collection provides various implications for the analysis. In the analysis process, the non-standardized and complex nature of data collected necessitates condensing. 79 This approach is advantageous as it dictates direct contact between the researcher and participants, incorporation of an adaptable approach within data collection and an inquiry process via provision of a better understanding pertaining to the issues affecting online shoppers. According to Bryman (2012), qualitative research is marked with adaptability in comparison to quantitative research, as qualitative research allows flexibility achieved in insight and provision of a summary of undesired results, which would necessitate further examining. Moreover, Creswell and Clark (2007) state that qualitative research seeks the participants to think and identification of the most viable responses. Nonetheless, Krathwoh (1997) believes that the main disadvantage of this model concerns the generalization of findings which vary depending on the extraction and interpretation of the data (Malhotra and Birks, 2007).

3.4.2 QUANTITATIVE APPROACH

According to Rasooli (2006) the quantitative approach involves selectivity and distance in relation to the research object. Moreover, it entails the search for knowledge that enhances measurement, and description and provides further explanation of the phenomena of reality. Oats (2006) posits that its constructive purpose aims at establishing relationships among measurable variables. According to Hussey and Hussey (1997), the quantitative research approach is based on provision of objective and representative results un-influenced by the researcher. Quantitative methods place more emphasis on numerical results as they seek to

minimize human factor influence. For instance, in the distribution of large-scale and formal questionnaires in an impersonal manner, the responses are duly coded via incorporation of statistical analysis (Malhotra, 2007). Manheim and Rich (1995) claim that quantitative research seeks to enhance direct retrieval of primary data from a provided sample that supports in the creation of inferences about the larger population. Additionally, the data retrieved is utilized in validating or disapproving the hypotheses (Malhotra and Birks, 2007). Quantitative research assists the researcher in testing the researcher’s validity and reliability via utilization of statistical methods (Saunders, Lewis and Thornhill, 2009). This provides a shortcoming resulted from the situation when complex information retrieved that may contain rich details is eliminated through incorporation of summative measures. Likewise, quantitative methods can produce representative data. However, this provides a shortcoming as it synthesizes the complex information into a summary. This leads to a neglect of the minute details and riches of participant’s behaviour, as they are hard to quantify (Rubin and Rubin, 1995). Contrastingly, quantitative research shows certain levels of richness as it contributes to the addition of more details to data. Nevertheless, the data represented is unclear and thus remains questionable (Kratwhoh, 1997). Moreover, quantitative research helps in compromising on the identified ambiguity and contradictions leading to the provision of alternative explanations (Denscombe, 2003). Therefore, the current study will incorporate quantitative research in order to ascertain results based from a greater numerical foundation of knowledge that will justify the overall analysis to a variety of measurable variables. In fact, quantitative research will deliver a better objective or overview of sharing video content without any linkage to the individual belief of the researcher. As seen, in table below is a detailed summary of qualitative research, quantitative research and the current study.

TABLE 3 SYNOPSIS

	Qualitative	Quantitative	My Research
Related to Objective	Identified by the proximity to the object	Selectivity and distance in relation to object	The current study is primarily quantitative in the sense that the researcher aims at converting raw data into figures and statistics without any link to the researcher’s beliefs or points of view. The phenomenon studied in the

			current research is not personal or subjective; it is existent in the world with or without the researcher.
Sampling	Small	Medium – Large	Macefield (2009) explicates that Power analysis can be performed after a test has been performed using the actual study data, when this is known as post hoc power testing. More usefully, it can also be performed before the test using results data from pilot studies or previous studies that are similar in nature , this is known as priori power testing. Adopting a priori test A sample size of 60 participants was used in relation to Berger (2011) which used 40 participants in a second experiment to understand how arousal increases social transmission of information.
Research Question	How and Why	What	The current study seeks to ask questions about the phenomenon and what shapes it or makes it what it is. The current study searches for defining the phenomenon through figures and statistics.
Aims	Understanding through first experience and quotations of actual conversation	Establishing relationships among measurable variables	The current study explores what the phenomenon is through converting facts into figures and statistics which are used to understand the relationships between variables.
Methods	Predetermined	Hypothesis	The current study will test a few hypotheses. To test whether the hypotheses are valid, quantitative data will be collected.
Data	Various implications	Statistical	The data gathered via a questionnaire and facial expression analysis will be

			converted into figures and statistics which will be interpreted in an objective way .
--	--	--	--

3.5 INDUCTIVE AND DEDUCTIVE APPROACHES

A researcher may decide to follow either a deductive or inductive approach depending on several factors, such as the emphasis of the research or the nature of the research topic. These approaches dictate the direction of the research, that is, either beginning with the formulation of a hypothesis towards the data collection and analysis to testing the hypothesis, or from data collection and analysis to the formulation of hypotheses based on the data. According to Wilson (2010), a deductive approach is one which is concerned with hypothesis (or hypotheses) development based on an existing theory, and then a study is designed to test the hypothesis. A deductive approach generally involves deducing conclusions from premises or propositions and, in most cases, it begins with the expected pattern and it is tested as per the observations. In this approach, reasoning moves from a more general to a more particular observation and ultimately refutes or confirms the theory being tested. The opposite is true for the inductive approach to research. There are several criteria that can determine if a deductive or inductive approach is suitable for a study. The nature of the research topic is important in this context. For instance, a topic on which there exists a wealth of literature from which one can create a theoretical framework and hypothesis is better tackled through a deductive approach (Bryman and Bell, 2011). However, in the case of a new research topic that is still generating debate, and which has scant literature from which the researcher can derive a hypothesis and theoretical framework, it is best to follow an inductive approach by first generating data and analysing and then reflecting upon whatever theories the data may suggest. An inductive approach requires an in-depth understanding and competent knowledge of the research idea, which is instrumental in the formulation of alternative explanations of the problem. This approach involves reasoning, beginning with specific observations and then moving towards broader generalisations and theories. Unlike in a deductive approach, where arguments are usually based on laws, rules and accepted principles, arguments are made based on observation through an inductive approach. Hence,

an inductive approach is best adopted in cases where resources are scarce, more time is needed to complete the study, and when risk is acceptable. Whereas a deductive approach is best adopted when there is an abundance of literature on the research topic, a short time to complete the study, as well as a minimisation of risk. However, both the inductive and deductive approaches can be used in a qualitative study (Myers, 2013) because, although hypothesis development and testing are claimed to be typical of a deductive approach, they are neither the exclusive preserve of a quantitative study nor the sole ways that deductive reasoning can be employed. Mostly facial expression analysis and questionnaire data will be incorporated and will be aimed at testing a hypothesis. This will correspondingly entail a deductive approach to the study, which will be initiated with the presentation of a theory and involve the examination of theoretical postulates utilising empirical data. Therefore, this thesis will utilise a deductive approach to research, in addition to using the quantitative methodology. (Bryman, 2012). Furthermore, the limited time is another reason for applying a deductive approach, because an inductive study is more exploratory and is connected with a long process of collecting and analysing data in order to develop a theory from it, while a deductive approach is narrower and investigates a specific theory or hypothesis (Bryman and Bell, 2011).

3.6 QUERY-BASED TECHNIQUES FOR MEASURING EMOTIONS

Query-based techniques such as questionnaires and surveys are some of the easier evaluation methods available (Wilson, 2002). Online surveys are also becoming more popular (Herrero and Meneses, 2006) as they provide access to a variety of individuals without there being a need to know postal details. Response rates for postal questionnaires can be low, meaning that either smaller samples are available for analysis or large numbers of questionnaires need to be distributed (Edwards et al., 2002). Higher response rates are possible with online surveys as respondents often forward details to others (Oats, 2006). However, one of the major limitations of surveys and questionnaires is the subjective nature of the responses (Oats, 2006 ; Saunders, Lewis and Thornhill, 2009). Another query-based technique is to interview the user after they have completed a task. However, user responses can be socially biased, in that participants offer the researcher information they think is wanted, rather than describing the reality (Wilson, 2002).

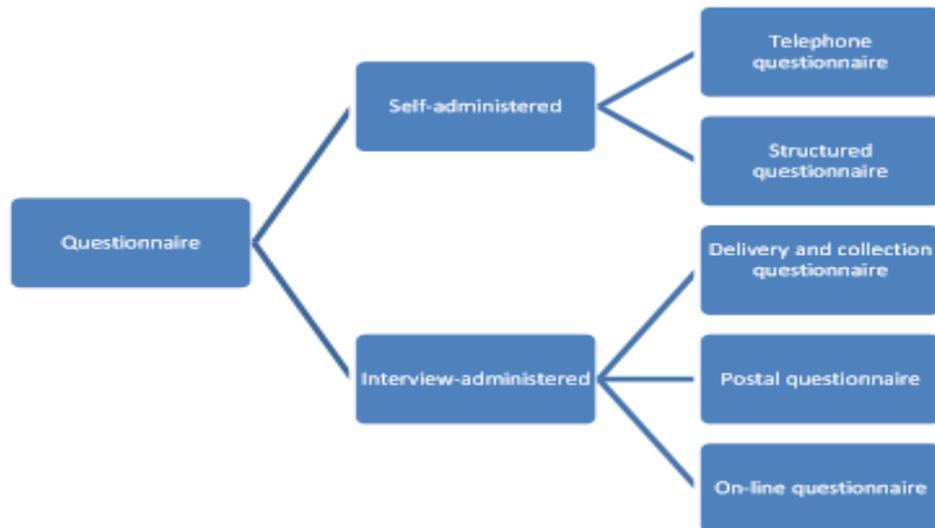
In specific reference to emotions the validity of self-reports is sometimes put to question. Robinson and Clore (2002) concluded that the degree to which self-reports are valid varies by the type of self-report. Specifically, self-reports of current emotional experiences are likely to be more valid than are self-reports of emotion made somewhat distant in time from the relevant experience (Robinson and Clore, 2002). In a practical study, for example, Barrett et al., (1998) asked men and women to report on their emotional traits “in general” as well as on their emotional reactions to events in daily life. Sex differences in emotional traits were prominent and large, whereas sex differences in daily experience were quite meagre and inconsistent, suggesting that trait reports of emotion are more biased (in this case by gender stereotypes) than reports made directly after an event. Conceptually similar findings have been reported when asking individuals to estimate their past or likely future responses to emotional events on the basis of such evidence for bias. Robinson and Clore (2002) concluded that self-reports of one’s current experience (“online”) are likely to be more valid than self-reports concerning past, future, or trait-related experiences of emotion.

Since Self-reports of emotion are likely to be more valid to the extent that they relate to currently experienced emotion it’s on this basis a web-questionnaire method will be used for this study in which participants would watch a video stimulus and be asked questions that would elicit their emotional responses in conjunction with facial expression analysis.

3.7 QUESTIONNAIRE TYPES

Questionnaires in general are often used as a method in a survey research strategy but are also associated with other research strategies such as an action research, case study or design and creation (Saunders , Lewis and Thornhill, 2009) . According to Saunders , Lewis and Thornhill (2009, p. 599) a questionnaire is “all techniques of data collection in which each person is asked to respond to the same set of questions (sometimes called items) in a predetermined order” Based on this definition, some forms of questionnaires include, structured interviews, phone questionnaires, self-administered etc as depicted below:

Figure 12 Questionnaire Types



In the diagram above an Interviewer-administered questionnaire includes ‘telephone questionnaire’ (those that the interviewer contacts the respondents and asks the questions over the phone which is widely used for market research) and ‘structured interview’ (those that interviewer meets the respondent face to face and asks the questions physically). In terms of self-administered, the questionnaires are placed in ‘delivery and collection’ (which is delivered to respondent individually), ‘postal questionnaire’ (respondents receive the questionnaire by post and return it once it has been completed) and ‘on-line questionnaire or web-based’ (using email or the Internet to send and receive the questionnaire). Apart from the differences in term of questionnaire types, there are also two kinds of questions used in survey which are open-ended and closed-ended questions. Any answer can be given by respondents in open-ended questions while respondent should choose from the fixed set of responses in close-ended questions.

3.7.1 LIKERT ITEM SCALE

A Likert scale is a standard of measurement that is frequently used in survey questionnaires, which has been developed for the measurement of a person’s attitudes (Likert 1932). Four primary scales are used in questionnaires: nominal, ordinal, interval and Ratio scale, and each scale will be discussed individually. The nominal scale is a procedure for assigning a number to an object, property or concept in order to identify the thing to be measured (Burns and Bush, 2010). This scale can be based on natural categories like gender (male or female) or artificial categories like education (did not attend school, primary school, elementary school,

secondary school, bachelor's degree, master's degree, PhD degree and above). The ordinal scale involves the ranking of individuals, attitudes or items along the continuum of the characteristic being scaled. For instance, an item may ask students to rank ten types of classroom activities from most to least interesting (Burns and Bush, 2010). It is only with an interval scaled data that researchers can justify the use of the arithmetic mean as the measure of average. The interval or cardinal scale has equal units of measurement, thus making it possible to interpret not only the order of scale scores but also the distance between them (Burns and Bush, 2010). However, it must be recognised that the zero point on an interval scale is arbitrary and it is not a true zero. Thus, a statement and its rating are said to constitute a single item of the scale. In fact, the statement for the scale may be worded in a positive or negative manner, although sometimes the number of rating options is. In its most basic forms, for example, the scale consists of statements with a dichotomous rating (agree/disagree) option (Oats, 2006). The scale may also consist of bivalent labels that are symmetric and range from strongly agrees to strongly disagree. Moreover, most of the time these options are numbered, consecutively, from one to a maximum of nine. Nevertheless, there are studies that have numbered this scale up to 11 (Russell and Bobko, 1992), but the rating options numbered 1 to 5 and 1 to 7 are the most common (Burns and Bush, 2010). These interval scales may be either numeric or semantic.

The highest level of measurement is a ratio scale. This has the properties of an interval scale together with a fixed origin or zero point. Examples of variables which are ratio scaled include weights, lengths and times. Ratio scales permit the researcher to compare both differences in scores and the relative magnitude of scores (Burns and Bush, 2010). For example, a scale like age can be zero, and it makes sense to think of four years as twice as old as two years. Researchers are often concerned with the differences among these scales of measurement because of their implications for making decisions about which statistical analyses to use appropriately for each. At times, they are discussed in only three categories: nominal, ordinal, and continuous (Burns and Bush, 2010). This study adopted a 5-likert scale to ensure robustness.

3.7.2 WEB – BASED QUESTIONNAIRE

This study aims to examine online video virality by understanding the emotions elicited from watching selected viral and non-viral football related videos hence, as an objective strategy the web-based questionnaire will be the most appropriate method for data collection. In a web-based questionnaire the researcher places a question on the web and respondents are asked to complete and submit it electronically. As with any method there are some disadvantages in relation to using the web-based questionnaire approach. There are two main areas of concern: coverage and response issues (Saunders , Lewis and Thornhill, 2009). The first challenge, which is not applicable for this study, involves unequal access to the Internet. This scenario was partially mitigated with students who partook in the study in a controlled lab environment where internet facilities were available and uninterrupted with broadband issues.

The second critical issue is with getting a nonresponse (Neuman, 2003). **This major problem can affect the result and the findings may not be generalisable.** This issue becomes more important when the sampled respondents do not respond however, all respondents who partook in the study answered as appropriate. Furthermore, Oates (2006) notes that there are many ways of designing questions and response formats, these include but are not limited to yes/no answers, quantity questions, agree or disagree with a statement, degree of agreement or disagreement - the **'Likert scale'** (See 3.7.1). In relation to the thesis **the following web questionnaire was used for the study.**

TABLE 4

JUSTIFICATION TABLE

Questions	Justification and Content Validity
<p>1. How best will you describe yourself? *</p> <p><input type="radio"/> Salford City FC Fan</p> <p><input type="radio"/> Football Fan</p> <p><input type="radio"/> Non Football Fan</p>	<p><i>Tajfel (1979) proposed that groups (e.g. social class, family, football team etc.) which people belonged to are an important</i></p>

	<p><i>source of pride and self-esteem.</i></p> <p><i>In-group vs. Out-group membership has an influence on the type of content that you spread.</i></p> <p>Guadago et al., (2013)</p>
<p>2. On a scale of 1-5 with 1 being the lowest and 5 the highest how will you rate your commitment to your football club (Applicable only to football fans, skip to the next question if you are not).</p> <p style="text-align: center;">1 2 3 4 5</p> <p style="text-align: center;">Least committed <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most committed</p>	<p><i>In-group vs. Out-group membership has an influence on the type of content that you spread.</i></p> <p>Guadago et al., (2013)</p>
<p>3. What is your age?</p> <p><input type="radio"/> Under 20 Years</p> <p><input type="radio"/> 21 - 30</p> <p><input type="radio"/> 31 - 40</p> <p><input type="radio"/> 41 - 50</p> <p><input type="radio"/> 51 - 60</p> <p><input type="radio"/> 61 and above</p>	<p><i>Gender and age influence online sharing behaviour.</i></p> <p>Hargittai, E and Walejko, G (2008).</p>
<p>4. How frequently do you watch YouTube videos? *</p> <p><input type="radio"/> Daily</p> <p><input type="radio"/> Weekly</p> <p><input type="radio"/> Less often</p>	<p><i>Frequency with which you receive viral messages.</i></p> <p>Camarero, C. and San Jose, R (2011)</p>

<p>5. What is your gender? *</p> <p><input type="radio"/> Male</p> <p><input type="radio"/> Female</p> <p><input type="radio"/> Other</p>	<p><i>Emotions, gender and culture influence virality.</i></p> <p>Dobele et al., (2007).</p> <p>Gender and age influence online sharing behaviour.</p> <p>Hargittai, E. and Walejko, G (2008).</p>
<p>6. Where are you based? *</p> <p><input type="radio"/> United Kingdom (UK)</p> <p><input type="radio"/> Europe (Non-UK)</p> <p><input type="radio"/> Other</p>	<p><i>Emotions, gender and culture influence virality.</i></p> <p>Dobele et al., (2007)</p>
<p>7. How likely will you be to share this online video with friends, family members, and co-workers? *</p> <p style="text-align: center;">1 2 3 4 5</p> <p>Least likely <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most likely</p>	<p><i>The question was extracted from Berger (2011). Berger also identified social dynamics as key for content sharing.</i></p> <p>network dynamics influences the success of viral marketing. As does the product category, price and time of recommendation.</p> <p>Leskovec, J., Adamic, L.A. & Huberman, B.A (2007).</p> <p><i>Your social capital influences your likelihood to pass on a message.</i></p> <p>Camarero, C. and San Jose, R (2011).</p>

<p>8. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" * being the highest to what degree of intensity did the video make you happy?</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Happy</p>	<p><i>Positive content spreads faster than negative. Emotional arousal is key.</i></p> <p>Berger, J. & Milkman, K.L.(2012).</p> <p>Positive emotions influence virality.</p> <p>Jenkins, B (2011).</p> <p><i>Motivations to share included:</i></p> <p>happiness/joy, resentment, advocacy, economic incentives.</p> <p>Roy (2011).</p>
<p>9. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" * being the highest to what degree of intensity did the video make you Angry?</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-Applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Angry</p>	<p><i>Positive and negative emotions spread equally.</i></p> <p><i>High arousal emotions get shared more</i></p> <p>Nelson-Field, K., Riebe, E. and Newstead, K (2011)</p>
<p>10. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" * being the highest to what degree of intensity did the video make you sad?</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-Applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Sad</p>	<p><i>Positive and negative emotions spread equally.</i></p> <p><i>High arousal emotions get shared more</i></p>

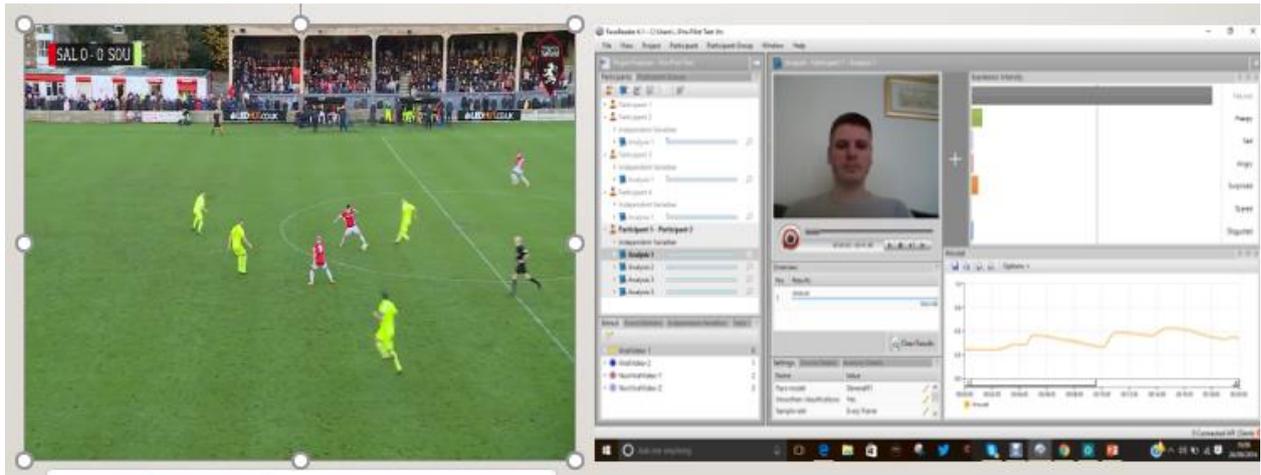
	Nelson-Field, K., Riebe, E. and Newstead, K (2011)
<p>11. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" being the highest to what degree of intensity did the video make you scared? *</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-Applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Scared</p>	<p><i>positive and negative emotions spread equally. High arousal emotions get shared more</i></p> <p>Nelson-Field, K., Riebe, E. and Newstead, K (2011)</p>
<p>12. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" being the highest to what degree of intensity did the video make you disgusted? *</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-Applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Disgusted</p>	<p><i>positive and negative emotions spread equally. High arousal emotions get shared more</i></p> <p>Nelson-Field, K., Riebe, E. and Newstead, K (2011)</p>
<p>13. On a scale of 0-5 with "0" being non-applicable, "1" being the lowest and "5" being the highest to what degree of intensity did the video surprise you? *</p> <p style="text-align: center;">0 1 2 3 4 5</p> <p>Non-Applicable <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> Most Surprised</p>	<p><i>Amusement or surprise is key for sharing of content.</i></p> <p>Berger (2011). <i>Emotional tone influences spread</i></p> <p>Eckler, P. & Bolls, P (2011).</p>

3.8 FACEREADER / FACIAL EXPRESSION ANALYSIS

Benta et al. (2004) described FaceReader as a system for fully automatic real time facial expression analysis developed by VicarVision and commercially available since 2007. It is currently used worldwide for numerous (consumer) behaviour studies. The software tool can process still images, video and live camera feeds and produces approximately 15 analysis results per second on a modern PC, allowing it to be used in real-time. FaceReader can classify expressions corresponding to one of the 6 basic emotions as defined by Ekman (1992) plus neutral and classifies the emotional valence of the expression and some personal characteristics like gender, age and ethnicity. A detailed description of the technology used in the FaceReader is beyond the scope of this thesis.

The interest in the assessment of spontaneous displayed emotions is very important for real-time human-computer applications, as emphasized in the literature . However, the number of existing real-time non-invasive emotion assessment tools described in other papers that recognize emotional facial expressions is small and lack performance evaluations for spontaneous elicited emotions. FaceReader is one of the few publicly available automatic facial expressions recognition systems with advanced analysis and reporting functions (Benta et al.,2009). According to studies done by Terzis, Morides and Economides (2010) the FaceReader has the capability to measure emotions with an efficacy of over 87% and is highly recommended to be a tool used for the amelioration of computer aided design. However, studies suggest that **“Disgusted” and “Angry” are two emotions that FaceReader recognizes less effectively**. Most of the times FaceReader measures simultaneously these two emotions, the researchers agree only with the presence of an Angry emotion. Some movements of jaw, mouth and nose confuses the FaceReader accuracy. Additionally, many times FaceReader measures an angry emotion simultaneously with a neutral one, but neutral was the only emotion confirmed by the researchers. **Nevertheless, the high efficiency rate of measuring emotions was a determining factor in choosing this approach for measuring emotions elicited from watching videos in this study as opposed to other studies methods such as eye tracking and retrospective emotion think aloud**, the fact that the facial expression analysis study will go in conjunction with an online web questionnaire.

Figure 13 Facial Expression example



3.9 VALIDITY

Salkind (2010) defines validity as to the degree to which a measure accurately taps the specific construct that it claims to be tapping. Salkind (2010) explains that validity addresses the question of whether test results provide the intended information, as such, validity evidence is primary to any claim of utility. A measure can be perfectly reliable, but it is useless if the intended construct is not being measured. However, the exact nature of validity as used in both social and educational research is still causing so much debate since there is not one definition that is considered ideal. Different scholars define validity differently, but the common concept they all agree on is the fact that there should be a level of accuracy in measuring a variable. They aim to answer whether a certain indicator measures what it is meant to measure and if it the best choice of indicator for the said variable. One of the most cited definitions of validity is that of Winter's (2000, p.4): "An account is valid or true if it represents accurately those features of the phenomena that it is intended to describe, explain or theories." Many authors have come up with other replacement terms and definitions, but all revolve around the same concept.

However, validity is not to be confused with precision. The more precise a measure, the more difficult it is to achieve high levels of validity. For instance, we could measure the time in milliseconds a child takes to complete a test that is supposed to last for one hour. The extra degree of precision in this case is highly unlikely to generate a greater degree of validity. Similarly, even in most qualitative researchers where a high degree of accuracy is desired, over precision is avoided since such results can confound or obscure the general purposes of

research. Nevertheless, validity is not a unitary concept as Hitchcock (2012) suggests. There exist many perceptions of validity, and they vary depending on the research topic and this may even change depending on the specific stage within the research. This depends on the researcher and their beliefs with regards to what stage of the research process requires validation. This can be in the measurement, scores, instruments, or observers rather than the entire research process.

Maxwell (1992) identifies five types of validity as they relate to different stages in the research process: descriptive validity, interpretive validity, theoretical validity, generalisability and evaluative validity. Descriptive validity measures the accuracy of facts as reported by the researcher and thus acknowledges the essential role of the researcher in the research process (Waltz et al., 2005). It is concerned with the first stages of research that involve data collection. If different observers or data collection methods produce different accounts of the same situation or events, then there is a question of descriptive validity (and consequently other types of validity as well) of the methods and accounts. Researchers should, therefore, consider doing a pilot study to ensure that validity is not compromised in these initial stages. Qualitative research, however, acknowledges the fact that in studying human systems, contradiction is inevitable and should, therefore, be investigated further. However, this would be totally unacceptable in a quantitative approach.

Regarding interpretive validity, a measure is only valid or true if the actors or participants can confirm and recognise the findings of a research. It is a value of the extent to which an interpretation is representative of an understanding of the underlying group (Hitchcock, 2012). A valid measure should be able to respect the perspective of the participants from which data is collected. This mostly applies to qualitative research since quantitative research is much more objective and, therefore, it would be impossible to think that a reasonably constructed interpretation in a quantitative study would be rendered invalid based on failure to be confirmed by the actors.

Theoretical validity measures the extent to which a theoretical explanation derived from findings of the research is consistent with the data. This type of validity is very specific to the research itself and to the mental and emotional constructs of the researcher. It is most commonly used for qualitative research approaches (Waltz, et al., 2005). **Evaluative validity measures the extent to which an evaluation framework can be implemented to the objects**

of the study. Evaluation in research is inevitable and, therefore, both the qualitative and quantitative approaches need to take this form of validity seriously as it contributes to the overall validity of the study (Waltz, et al., 2005).

Generalisability refers to the degree of reproducibility of the study where the researcher can generalise the account of a specific event, context or populace to another separate time, setting or context (Maxwell, 1992). Maxwell (1992) classifies it into internal generalisability and external generalisability. Internal generalisability is the application of the same results of the study within the underlying setting or group and the latter with reference to generalisability outside the confines of the study population, time, setting, or context. Maxwell also claims that internal generalisability is more important than external generalizability to a qualitative research approach.

A central part in the development of any scale is establishing its content validity; construct validity, uni-dimensionality and reliability. Content validity has been defined by various authors (Wynd, Schmidt and Schaefer, 2003; Waltz, et al., 2005) but the consensus among them is that content validity is a measure of the degree to which a selected sample represents every single element in a sample. It is important to consider in both qualitative and quantitative approaches since it determines the accuracy of the research in general. Sample representation is a concern for quantitative research.

Construct validity refers to the degree with which a test measure adequately measures what it claims to be measuring. Researchers must be careful in selecting their indicators since these are what will be used in testing of the hypothesis and ultimately determining the validity of the research along with other measure of validity (Henson, 2001). Alternatively, Salkind (2010) defines construct validity as the overarching principle in validity. **It asks, Is the correct construct being measured?** One of the principal ways that construct validity is established is by a demonstration that tests are associated with criteria or other tests that purport to measure the same (or related) constructs. Affirmatively, Cohen and Swerdlik (2009) defined construct validity as a judgment about the appropriateness of inferences drawn from test scores regarding individual standings on a variable called a construct. A construct is an informed, scientific idea developed or hypothesized to describe or explain behaviour.

Several procedures may be used to provide different kinds of evidence that a test has construct validity. The various techniques of construct validation may provide evidence, for example as in this thesis where test scores correlate with scores on other tests in accordance with what would be predicted from a theory that covers the manifestation of the construct in question. Evidence for the construct validity of a test may converge from several sources, such as other tests or measures designed to assess the same (or a similar) construct. Thus, if scores on the test undergoing construct validation tend to correlate highly in the predicted direction with scores on older, more established, and already validated tests designed to measure the same (or a similar) construct, this would be an example of convergent evidence.

A validity coefficient showing little (that is, a statistically insignificant) relationship between test scores and/or other variables with which scores on the test being construct-validated should not theoretically be correlated provides discriminant evidence of construct validity (also known as discriminant validity). Oates (2006) expatiates further that a research must assess if its measuring what it thinks its measuring via its questions. For example, a multiple-choice test might be designed to assess students reasoning skills but might really measure how a quickly they can read. To test for construct validity, it may be necessary to correlate responses against other responses in the questionnaire. For example, if a researcher thinks that dissatisfaction with an IT department correlates with a high number of calls to the IT-help desk, the researcher could assess if respondents who stated that they were dissatisfied did indeed make calls to the help desk.

3.9.1.1 RELIABILITY

Salkind (2010) argues that reliability provides a framework for thinking about and quantifying the consistency of a test. Even though reliability does not directly address constructs, it is still fundamental to measurement. Typical methods used to estimate test reliability include test-retest reliability, alternative forms, split-halves, inter-rater, stability reliability and internal consistency (Rosenthal and Rosnow,1991; Salkind, 2010). Reliability testing deals with three main areas, i.e. equivalence, stability over time and internal consistency. Test-retest reliability refers to the sequential stability of a measurement from one session to another. Moreover, the procedure involves administering a test to a group of respondents then administering the same test to the same individuals later. The correlation between the same tests given at

different occasions will define the test-retest reliability. However, this technique has its own limitations (Rosenthal and Rosnow, 1991). For instance, if the duration between the two tests is too short, the respondents may know from the first test what to say the next time the same test is administered and, therefore, may provide biased information. Additionally, if the duration is too long, the respondents may have had experiences which change their opinions, feelings and attitudes about the behaviour being studied. This effect is referred to as maturation.

“Alternative forms technique” as used in estimating reliability is similar to the test-retest technique except that different measures of a variable are collected at different times. If the correlation between the two results are low, then it will indicate that there exists a considerable error in measurement. Several limits to the test-retest method also apply to the alternative form’s technique.

Split-half approach is another method used to test the reliability of a measurement whereby it is assumed that several items that measure a behaviour are available. Half of these items are joined to form a single new measure, and the other half is combined to form another new measure. This results into two new tests for two new measures, while testing the same behaviour. Unlike the previous two techniques, the split-half approach is carried out at the same time. The correlation between of the two halves should then be corrected to get the reliability coefficient of the whole test. The split-half method has an advantage over the test-retest and alternative form techniques since the effect of memory does not operate in this approach and the split halves are relatively cheaper and easy to get as compared to data obtained over time. The disadvantage of the split-half method is that the tests must be parallel measures, meaning the correlation will vary slightly depending on the way the items have been divided. Inter-rater reliability assesses the reliability of judgments or combined internal consistency of raters or judges used to measure behaviour. For instance, when two judges are used to assess ten subjects, the correlation between the ratings made by the two judges will determine the reliability of both judges in the specific situation. A compound reliability of both judges or raters, also referred to as effective reliability, is then calculated using the Spearman-Brown formula (Rosenthal and Rosnow, 1991).

Internal consistency is concerned with the reliability of the test components. It measures the consistency within the instrument and tries to answer the question of how well a set of items

measures a behaviour. In measuring emotions Levenson (2003) argued that it is important to distinguish between situations in which participants make emotional judgments (e.g., watching a video of a toddler getting bit by a python as being "5" on a 7-point sadness scale) and situations in which they experience sadness. In some cases, participants may experience sadness when viewing such a video, but their ratings in the latter case indicates that they perceive the video as having sad qualities but not that it makes them experience sadness. Thus, for studying the physiology of emotion on viral videos it is important to produce "real" emotional experience in participants.

Additionally, Levenson (2003) noted that researchers who enter into the study of the physiology of emotion immediately encounter the problem of how to elicit emotions in the laboratory. It is tempting to simply adopt some method of elicitation that has a modicum of a priori face validity and assume that this method will produce the full range of emotions of interest. Invariably, the investigator is faced with a frustrating trade-off between ecological validity and experimental control. Thus, tasks that are most like contexts in which human emotions typically occur (e.g. unrehearsed, minimally structured dyadic interactions between intimates) can be an experimental nightmare. **In contrast, tasks with very tight experimental control (e.g., directed facial actions, which give the experimenter precise control of which emotion is displayed on the face and when) are not very representative of the ways in which emotions usually occur.** Furthermore, the six emotions commonly studied in autonomic specificity research (anger, disgust, fear, happiness, sadness, surprise) are not equally accessible using the different elicitors.

McGinley and Friedman (2017) observed a notable issue in emotion research which is the duration of laboratory-induced emotions. This issue has important implications for statistical analysis, because some autonomic variables require lengthy durations to provide enough usable data points to avoid statistical violations. The most frequently used durations for emotion studies are responses averaged over thirty- to sixty-second intervals. However, averaging over 1/2 to ten-second intervals, and from 120- to 300-second intervals are also common. Another aspect of this issue is temporal variability among emotions; e.g., sadness tends to last longer than surprise, which presents challenges to using a standard time for emotion induction epochs within a study.

Finally, there is the issue raised about whether participants elicit "real" emotions or not. With the directed facial action task (Levenson and Ekman, 2002) the experimental demand to report the emotion constructed on the face is high, even if that emotion is not actually felt. With external visual stimuli such as slides and films, it is common for participants to feel no emotion but to report feeling emotions that represent their judgments of the emotional qualities of the stimuli. The "real-life" elicitors (staged manipulations and dyadic interactions) seem most likely to produce "real" emotions but not without incurring a number of costs, including loss of experimental control, appearance of complex sequences of emotions, and, in the case of staged manipulations, serious ethical and human participant's issues.

3.9.1.1 VALIDITY AND RELIABILITY OF THE FACEREADER IN RELATION TO DATA

Lewinski, Uyl and Butler (2014) explained that the validity and reliability of the FaceReader is based on (a) principles of computer algorithms, (b) psychological theories and (c) recognition studies. Computer algorithms code facial expressions according to a set of fixed rules that are invariably applied to each expression. Lewinski, Uyl and Butler (2014) explained that algorithms always follow a specific coding protocol, do not have personal biases (e.g. about gender, culture or age) and do not get tired. This research however noted that the algorithms in the technology cannot be said to be fully robust to adequately observe and encode data accurately equally among all races ; it was observed during the study that the technology had some difficulty calibrating people of darker skin sometimes leading two multiple calibrations. The effects of multiple calibrations will be explained further in this methodology section as it resulted in lab participants being more angry or less happy (p.121-122) and subsequently, when the final results tests were run there were instances where for some participants the ethnicity , age or gender the FaceReader specified were different from what could be adjudged subjectively by the researcher or what was also inputted in the web questionnaire.

The issue experienced with FaceReader is also more common place in the wider industry with other technologies. Harwell (2019) noted from a federal US study that Facial-recognition systems misidentified people of colour more often than white people - Asian and African American people were up to 100 times more likely to be misidentified than white men, depending on the particular algorithm and type of search. The study also revealed that women were more likely to be falsely identified than men, and the elderly and children were

more likely to be misidentified than those in other age groups. This study was able to offset or control the discrepancy pertaining to demographic data as it also relied on questionnaire or self-report data. The self-report was the validating criterion in this study and was used as the primary basis for the following demographics: Fan group, gender, age and location (p.117 – 118). Albeit, the Race or ethnicity was not collected via self-reports but alternatively was derived using the FaceReader which automatically tries to determine the ethnicity of the participants and also by the researcher subjectively determining the race or ethnicity by looking at the face of the participants in the video stimuli.

3.9.1.2 VALIDITY AND RELIABILITY OF THE FACEREADER IN RELATION TO FACS

Significantly, Skiendziel, Rosch and Scultheiss (2019) argued that Automated facial coding offers an attractive alternative to classic FACS coding as it drastically decreases the time needed for both learning and applying the method. Some researchers (e.g., Bartlett et al., 1999; Cohn and Ekman, 2005) even consider the former to have greater objectivity and reliability than the latter, because repeated analyses of the same material will always yield exactly the same result in the case of automated coding. Subjective coding bias and fatigue effects are completely absent. Thus, a well validated automated coding method has the potential to extend emotion research by making analysis of facial expressions more accessible and affordable. It is also important to state that the artificial intelligence that stands behind FaceReader does not have human free will and the unconstrained possibilities of making subjective choices. For example, running the FaceReader software twice on the same dataset will always give the same results. Furthermore, FaceReader is based on psychological theories and therefore the algorithms are built upon pre-existing knowledge such as one's which are stemmed from the theories propounded by Paul Ekman as evident in the literature review. Current research has shown that there is a high correlation between Action Units (AU) which is a derivative of FACS (Facial Action Coding System) and FaceReader Technology - where on average 80% of the emotional facial expressions are classified (Skiendziel, Rosch and Scultheiss, 2019). Additionally, other measures of validity, such as face validity; content validity and criterion-related validity all contribute to the overall construct validity of this research study.

A key issue identified in both literature and the study are problems with measuring facial expression when participants are interacting with a computer rather than a person. Despite the findings of Reeves and Nass (1996), people do not always respond the same when looking at a computer screen. The fundamental issue addressed above is with internal validity, thus, usually differences between experimental and the control group: If they were different, any subsequent measures might not be attributable to the manipulation of the experimental group. The research made the use of experimental groups, notably and in context, lab users (in-house) and PeoplePerHour Freelancers (remote users), who were test subjects made to watch the same video stimuli. The study however, found some significant difference between users who undertook the research remotely and in a lab environment (p.121-122). In relation to **content validity**, Oates (2006) explains that a given questionnaire must generate data about the concepts that a researcher is interested in or a well-balanced sample of the domain to be covered. For example, if a researcher is doing a study on understanding video virality, all the different aspects of the user's concept is covered by the questionnaire (i.e extent of emotionality, willingness to share, gender, age, etc). Oates (2006) advised researchers to consider using previously used questionnaires for adaptation. This research utilised a web questionnaire and provided a justification for the questions citing references and, in some instances, previously used questions in other related research studies (See section 3.7.2).

With regards to concurrent validity the key question is to ascertain if the correct construct is being measured (i.e emotions). Thus, the basis for construct validity in this thesis is established by a demonstration that tests are associated with criteria that purport to measure the same constructs (i.e emotional intensity obtained from web questionnaire and facial expression analysis). This thesis found evidence for discriminant validity (concepts or measurements that are not supposed to be related are unrelated) of the emotions data obtained from using facial expression analysis and a web questionnaire.

alternate-form reliability requires that each member of a representative sample respond on two alternate assessments (i.e. facial expression analysis and questionnaire survey). These alternate forms should have been built to be purposefully parallel in content (i.e. viral video stimuli) and scores produced (i.e. emotional intensity scores). The tests should be administered as close together as is practical, while avoiding fatigue effects. The correlation among these forms represents the alternate-form reliability. Higher correlations provide

more confidence that the tests can be used interchangeably (comparisons of means and standard deviations) will also influence this decision. As part of the research scope of the study, findings showed low correlations between the two testing methods, hence suggesting that the two methods cannot be used interchangeably (See Analysis 3).

3.10 EXPERIMENTAL DESIGN ADOPTED

CIRT (2018) explains that experimental design is concerned with the effect of the examination of the independent variable, where the independent variable is manipulated through treatment of interventions and the effect of interventions. CIRT (2018) identifies three basic types of experimental research designs. These include pre-experimental designs, true experimental designs, and quasi-experimental designs. The degree to which the researcher assigns subjects to conditions and groups distinguishes the type of experimental design. CIRT (2018) makes a distinction on the different types of true experimental designs. True experimental designs are characterized by the random selection of participants and the random assignment of the participants to groups in the study. The researcher also has complete control over the extraneous variables. McLeod (2017) identified three types of experimental designs: Independent measures, repeated measures and matched-pairs whilst Oates (2013) noted: one -group, pre-test and post-test, static group comparison, pre-test/ Post-test control group and Solomon four-group design. Some of the characteristics of the designs, pros and cons will be examined in the table below:

TABLE 5 **EXPERIMENTAL DESIGNS**

Design Type (Characteristics)	Pros	Cons	Does this study meet the criteria?
Independent Measures (Between groups). In this type of experimental design each condition of the	Avoids order effect as people participate in one condition only. If a person is involved in several conditions, there is	It usually involves a lot of participants. Differences between participants in the groups may affect results, for example; variations in	No, as this study requires the same set of participants.

<p>experiment includes a different group of participants. This is done by random allocation which ensures that each participant has an equal chance of being assigned to one group or the other.</p>	<p>a tendency for boredom or fatigue.</p>	<p>age, gender or social background. These differences are known as participant variables.</p>	
<p>Repeated Measures (Within groups). Each condition of the experiment includes the same group of participants.</p>	<p>As the same participants are used in each condition, participant variables (i.e., individual differences) are reduced.</p> <p>Fewer people are needed as they take part in all conditions (i.e. saves time).</p>	<p>There may be order effects. Order effects refer to the order of the conditions influencing the participants' behaviour. Performance in the second condition may be better because the participants know what to do (i.e. practice effect). Or their performance might be worse in the second condition because they are tired (i.e., fatigue effect). This limitation can be controlled using counterbalancing.</p>	<p>Yes, as all participants partake in both methods (i.e facial expression analysis and self-report (questionnaire) and are subject to the measurement of their emotions elicited from watching the same video stimuli.</p>

<p>Matched – Pairs.</p> <p>Each condition uses different but similar participants. An effort is made to match the participants in each condition. In terms of any important characteristic which might affect performance, e.g., gender, age, intelligence, etc.</p>	<p>Reduces participant variables because the researcher has tried to pair up the participants so that each condition has people with similar abilities and characteristics.</p> <p>Avoids order effects, and so counterbalancing is not necessary.</p>	<p>If one participant drops out, you lose 2 personal participants data.</p>	<p>No, the participants are the same in both conditions.</p>
<p>One – group, pre-test and post-test.</p> <p>The participants performance is measured, the researchers then apply some treatment, they then measure the participants performance again.</p>	<p>By comparing the before and after scores, the researchers can assess the effects of the treatment efficiently.</p>	<p>The researchers cannot determine if time have had an effect – the participant might have just gotten better with time without the researchers input.</p>	<p>No, the test condition is done in parallel and not using a pre-test and post-test approach.</p>
<p>Static group comparison. The</p>	<p>Difference in groups can be</p>	<p>If participants are not randomly assigned to the</p>	<p>No, as the treatment is</p>

<p>participants are divided into two groups. The researchers apply the treatment to one group and do nothing to the other group. The performance of both groups is then measured.</p>	<p>explained by the treatment.</p>	<p>two groups, any difference might be caused by other factors than the treatment.</p>	<p>applied to both groups.</p>
<p>Solomon four – group design. This design controls for the possibility of pre-testing affecting subsequent performance. Participants are randomly assigned to four groups. Using the Solomon four-group design, subjects are randomly assigned to one of four different groups. Two of the groups receive the treatment (i.e.</p>	<p>Researchers using this design can examine both the main effects of testing and the interaction of testing and treatment. The researcher is also able to examine the combined effect of maturation and history by comparing, (the post-test only control group) and (the pre-test control group).</p>	<p>It is expensive because of the number of participants needed. There is difficulty in introducing the treatment simultaneously for all groups.</p>	<p>No, participants are not randomly assigned to 4 groups.</p>

intervention) and two do not (i.e. control).			
--	--	--	--

CIRT (2018) determines that once the design has been determined, there are four elements of true experimental research that must be considered:

- **Manipulation:** The researcher will purposefully change or manipulate the independent variable, which is the treatment or condition that will be applied to the experimental groups. It is important to establish clear procedural guidelines for application of the treatment to promote consistency and ensure that the manipulation itself does affect the dependent variable.
- **Control:** Control is used to prevent the influence of outside factors (extraneous variables) from influencing the outcome of the study. This ensures that outcome is caused by the manipulation of the independent variable. Therefore, a critical piece of experimental design is keeping all other potential variables constant. For example, if participants were deemed intoxicated, they will not proceed with the study as it can influence the result outcomes.
- **Random Assignment:** A key feature of true experimental design is the random assignment of subjects into groups. Participants should have an equal chance of being assigned into any group in the experiment. This further ensures that the outcome of the study is due to the manipulation of the independent variable and is not influenced by the composition of the test groups. Subjects can be randomly assigned in many ways, some of which are relatively easy, including flipping a coin, drawing names, using a random table, categorisation or utilizing a computer assisted random sequencing.
- **Random selection:** In addition to randomly assigning the test subjects in groups, it is also important to randomly select the test subjects from a larger target audience. For example, if a researcher wanted to look at the impact of sleep on the test scores of 5th graders in a city, a sample of 5th graders would need to be randomly selected from the city's population in such a way that any 5th grader would have an equal chance of being selected for the study. This ensures that the sample population provides an

accurate cross-sectional representation of the larger population including different socioeconomic backgrounds, races, intelligence levels, and so forth.

Based on the characteristics, pros and cons of the experimental designs this study has adopted the within-groups approach. The same subjects (participants) were used to undertake the survey and facial expression analysis, which is invaluable to ascertain the validity of the methods and how the data results are interpreted holistically.

3.11 SUMMARY OF PARTICIPANTS

60 respondents filled both the online web questionnaire and undertook the facial expression analysis which was used as the main basis for the study. **The 60 respondents comprised 32 football fans and 28 non-football fans.** It is important to establish that not all football fans were fans of Salford City FC or Manchester United but fans of other teams such as Liverpool and Arsenal Football Club. The respondents comprised lecturers and students from the University of Salford as well as carefully selected respondents selected from a freelance website (www.peopleperhour.com).

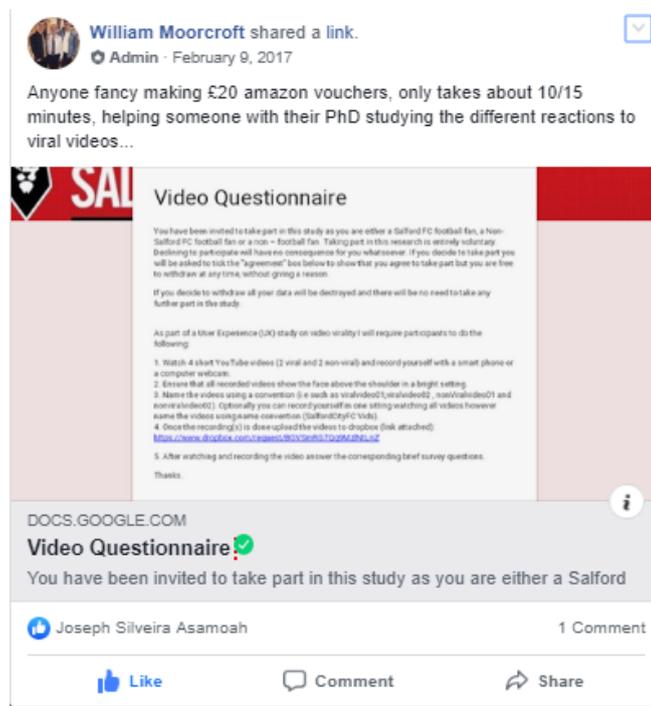
The choice to adopt PeopleHerHour was due to the fact the website has a large pool of respondents who make up the freelancing community and were willing to undertake the project albeit for a stipulated fee of £25. The initial scope of the research intended to solely rely on in-house participants using the laboratory settings. However, this was met with complications with regards to logistics (i.e availability of the labs, time scheduling for participants and suitable availability of the participants who will have to undertake both the web survey and facial expression analysis at a sitting). Conveniently, the FaceReader Software has the capability to analyse video stimuli both in-house and remotely. Remote analysis simply involved the participants accessing the instructions via the PeoplePerHour web portal, with the participants following specific recording instructions and submitting the videos through a repository web portal known as dropbox, the videos were consequently downloaded, and data analysed using the FaceReader software. Conversely, in Lab analysis involved participants coming to the Lab setting, where the moderator was present, and all computer logistics were setup.

Ultimately and in relation to this thesis, the second principal challenge was getting Salford City FC fans to undertake the project both in-house and remotely. The prime difficulty was getting adequate interested participants who were willing to undertake the study and do the study effectively. In order to source participants, the following attempts were initially made:

- Contact **Salford City FC** via the **Media and Communications manager**.
- Attend home games at the Moor Lane stadium (Salford City FC grounds) and **distribute participation leaflets**.
- Contact supporters who I knew personally who consequently contacted other supporters (**Peer Networking**). (E.g. the current marketing manager at Salford City FC).

My initial contact with the media and communications officer was successful. The communication officer who is also an administrator on the Facebook page posted the following research project on the **Salford City FC official group page**.

Figure 14 Research Invitation Sample



- There was very low turnout of the respondents and those who responded did not undertake the facial expression analysis part of the study which required video recording of themselves to elicit the emotional response. **This resulted in**

filtering and invalidating the respondent's data in order to meet objective 1b and 3 of the research studies.

- **Leaflets distributed** at the Salford City FC grounds returned no response.
- There were some participants who were obtained via networking and partook in a lab environment study, but these were not enough for a robust analysis on its own merit as **Salford City fans**.

Consequently, Salford City football fans were added to Football fans data for a more representative and significant analysis in terms of the sample size. Logically, the research does not believe it will skew the results negatively as Salford City Fans are football fans and the overall sample size of the Salford City participants was a negligible 5.

3.12 MATERIALS USED

To undertake the study, data collection was undertaken using two main methods which are objective and were run concurrently. Objective methods are quantitative in nature (i.e. research generates numerical data or information that can be converted into numbers) whilst subjective methods generate non-numerical data (Oates,2006). **The methods adopted for this study comprise the web questionnaires and facial expression analysis.**

Users who participated in this research study (both remotely and lab) had to be at a stationary sitting where they filled an online questionnaire which contained embedded video content comprising 4 video stimuli (2 viral and 2 non-viral). The participants in the labs were recorded using the Noldus FaceReader 6 platform. Participants were recorded through using the webcams provided while watching the video stimuli. They were aware of and agreed to be video recorded. Before each recording, they were instructed to position their head in the centre of the webcam's focus, reminded to maintain that posture and keep their hands on the keyboard during the entire recording. Participants were further informed that they had to watch 4 video stimuli and answer preceding questionnaires about the videos seen.

Remote participation involved filling the online questionnaire and having a self-recording which was subsequently uploaded into a Dropbox for further facial expression analysis). The use of video was primarily opted for as it has been used in several emotions studies and are typically considered as robust elicitors of emotion (McGinley and Friedman, 2017).

The online web questionnaire also measured each participant emotions and other variables such as the likelihood to share and how often they watch YouTube videos, whether they were football fans etc. In relation to the videos the first video stimulus was hypothesised to elicit mainly surprise whilst the second was happiness. The third and fourth videos were hypothesised to be neutral in nature and elicit very low emotional responses. The first video depicted a wonderfully struck long-range strike from the centre of the football field reminiscent of strikes from more renowned professional footballers.

Figure 16 Viral Video 1



Category: Memoryless video

The second video depicted Manchester United players acting for a pre-release trailer for a movie – “Independence Day Resurgence”.

Figure 15 Viral Video 2



Category: Popular viral video

The third video showed ex-Manchester United Defender Gary Neville discussing the promotion of Salford City FC.

Figure 16 Non- Viral Video 1



Figure 17 Non-viral Video 2

The fourth video depicted a celebratory scene as Salford City FC gained promotion.



All the videos were less than 4 minutes in length. The first and second video were chosen due to their widespread circulation – (Video 1 harnessing 64,476 views and 142 shares, Share Through Rate - 0.22%; Video 2 harnessing 257,757 views, 326 shares, Share Through Rate -

0.17%) and hypothesised ability to induce a measurable variation in the mean emotional intensities.

3.13 BREAKDOWN OF DEMOGRAPHIC DATA

The following is the breakdown of the demographic data of participants (individual and combined) as harnessed from the study comprising Football Fans and Non-Football Fans based on **Location, Gender, Age and Ethnicity (Race)**.

Figure 19a Individual Data Football Fans

Participant (Q)	Fan Group (Q)	Gender (Q)	Where are you based? (Q)	What is your age? (Q)	Ethnicity (F)
1	Football Fans	Female	United Kingdom (UK)	21 - 30	Caucasian
2	Football Fans	Male	Europe (Non-UK)	21 - 30	Caucasian
3	Football Fans	Female	Other	21 - 30	Caucasian
4	Football Fans	Female	Europe (Non-UK)	21 - 30	Caucasian
5	Football Fans	Male	United Kingdom (UK)	31 - 40	African
6	Football Fans	Male	Other	21 - 30	African
7	Football Fans	Male	Other	21 - 30	Caucasian
8	Football Fans	Male	Other	31 - 40	Caucasian
9	Football Fans	Female	United Kingdom (UK)	21 - 30	Caucasian
10	Football Fans	Male	United Kingdom (UK)	31 - 40	African
11	Football Fans	Female	United Kingdom (UK)	21 - 30	Caucasian
12	Football Fans	Male	United Kingdom (UK)	21 - 30	African
13	Football Fans	Male	United Kingdom (UK)	21 - 30	Caucasian
14	Football Fans	Female	United Kingdom (UK)	21 - 30	African
15	Football Fans	Male	United Kingdom (UK)	31 - 40	Caucasian
16	Football Fans	Male	United Kingdom (UK)	21 - 30	Caucasian
17	Football Fans	Male	Other	31 - 40	South Asian
18	Football Fans	Male	United Kingdom (UK)	31 - 40	Caucasian
19	Football Fans	Male	United Kingdom (UK)	31 - 40	Caucasian
20	Football Fans	Male	United Kingdom (UK)	31 - 40	Caucasian
21	Football Fans	Male	United Kingdom (UK)	31 - 40	African
22	Football Fans	Male	United Kingdom (UK)	31 - 40	African
23	Football Fans	Female	Other	41 - 50	African
24	Football Fans	Male	United Kingdom (UK)	21 - 30	East Asian
25	Football Fans	Male	United Kingdom (UK)	21 - 30	African
26	Football Fans	Male	United Kingdom (UK)	21 - 30	Caucasian
27	Football Fans	Male	United Kingdom (UK)	21 - 30	Caucasian
28	Football Fans	Male	United Kingdom (UK)	21 - 30	African
29	Football Fans	Male	United Kingdom (UK)	31 - 40	African
30	Football Fans	Male	United Kingdom (UK)	31 - 40	Caucasian
31	Football Fans	Male	United Kingdom (UK)	21 - 30	Caucasian
32	Football Fans	Male	United Kingdom (UK)	21 - 30	African

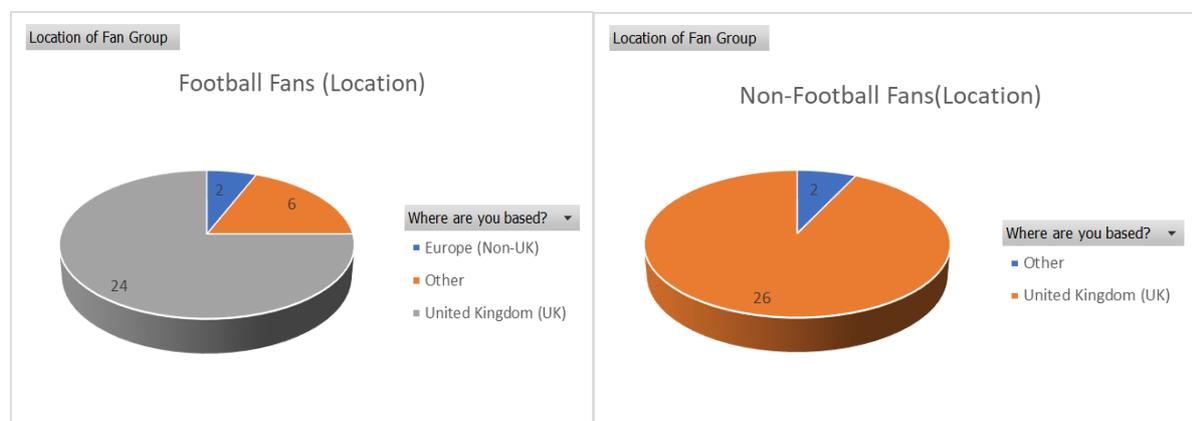
Individual Data Non – Football Fans

Participant (Q)	Fan Group (Q)	Gender (Q)	Where are you based? (Q)	What is your age? (Q)	Ethnicity (F)
1	Non Football Fan	Male	United Kingdom (UK)	21 - 30	Caucasian
2	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Caucasian
3	Non Football Fan	Male	United Kingdom (UK)	21 - 30	Caucasian
4	Non Football Fan	Male	United Kingdom (UK)	21 - 30	Asian
5	Non Football Fan	Female	United Kingdom (UK)	21 - 30	South Asian
6	Non Football Fan	Female	United Kingdom (UK)	21 - 30	African
7	Non Football Fan	Female	United Kingdom (UK)	21 - 30	African
8	Non Football Fan	Male	United Kingdom (UK)	21 - 30	Caucasian
9	Non Football Fan	Male	United Kingdom (UK)	21 - 30	African
10	Non Football Fan	Female	United Kingdom (UK)	21 - 30	Caucasian
11	Non Football Fan	Male	United Kingdom (UK)	31 - 40	Caucasian
12	Non Football Fan	Male	United Kingdom (UK)	31 - 40	Caucasian
13	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Caucasian
14	Non Football Fan	Female	United Kingdom (UK)	21 - 30	Eastern Asian
15	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Eastern Asian
16	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Caucasian
17	Non Football Fan	Female	United Kingdom (UK)	21 - 30	African
18	Non Football Fan	Female	United Kingdom (UK)	21 - 30	African
19	Non Football Fan	Female	United Kingdom (UK)	21 - 30	Caucasian
20	Non Football Fan	Male	United Kingdom (UK)	31 - 40	Caucasian
21	Non Football Fan	Female	United Kingdom (UK)	31 - 40	African
22	Non Football Fan	Female	United Kingdom (UK)	41- 50	African
23	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Caucasian
24	Non Football Fan	Female	United Kingdom (UK)	31 - 40	Caucasian
25	Non Football Fan	Female	United Kingdom (UK)	21 - 30	Caucasian
26	Non Football Fan	Male	Other	21 - 30	African
27	Non Football Fan	Male	Other	21 - 30	Caucasian
28	Non Football Fan	Male	United Kingdom (UK)	21 - 30	African

Do note that the ethnicity data is derived from observations from the FaceReader Software tool and was not incorporated into the self-report (Questionnaire) web form which is used as the validating criterion in the study. Due to Ethnicity being omitted from the self-report a criterion validity of the ethnicity could not be established. Additionally , the limitations of the FaceReader in relation to accurately evaluating the racial groups of participants are discussed in section 3.9.1.1. The FaceReader classifies ethnicity based on Caucasian , African and , South and Eastern Asian.

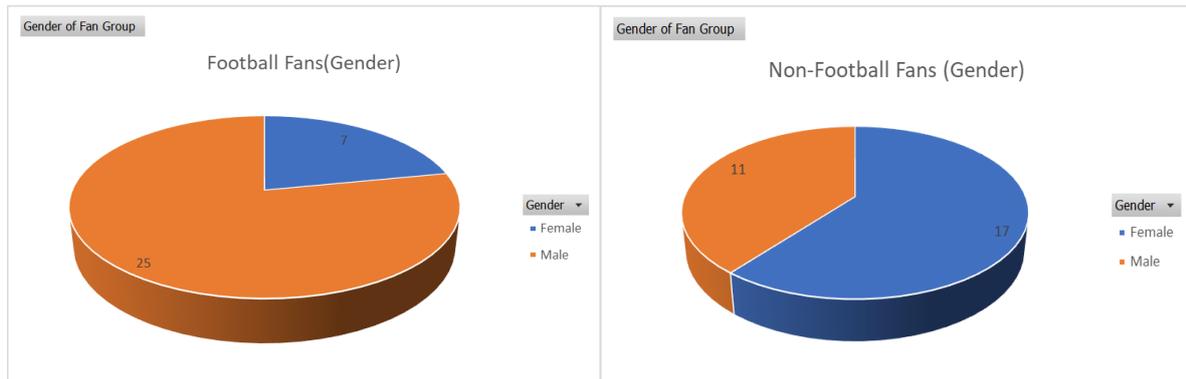
Figure 19b Combined Demographics

Location



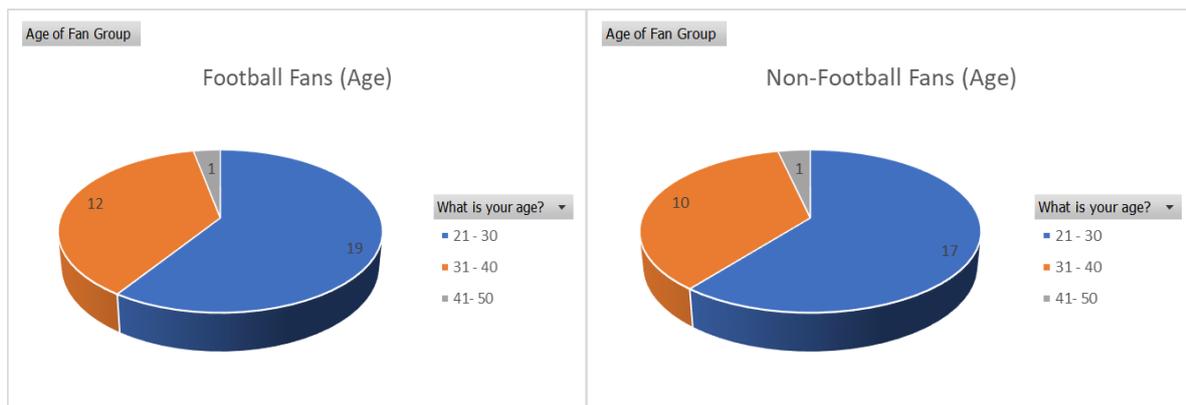
Based on the data collated, majority of the football and non-football fans surveyed for the study were based in the UK (83.33%).

Gender



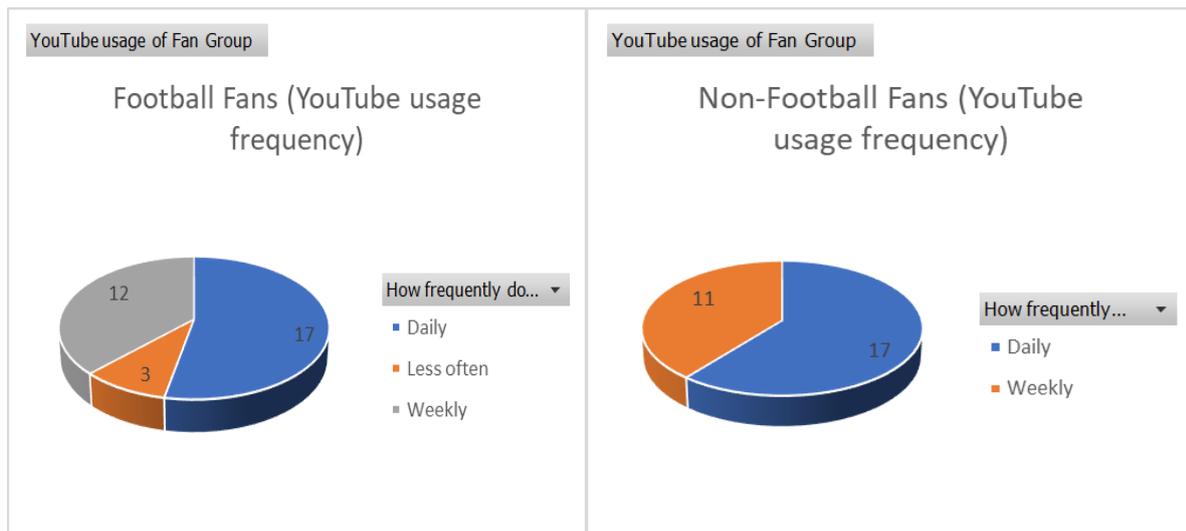
Based on the data collated, majority of the football fans surveyed for the study were males whilst non-football fans were females.

Age



Based on the data collated, majority of football fans and non-football fans were those in the age ranging from 21-30 (60%).

YouTube Usage Frequency



Based on the data collated, majority of football fans and non-football fans use YouTube daily (56.66%).

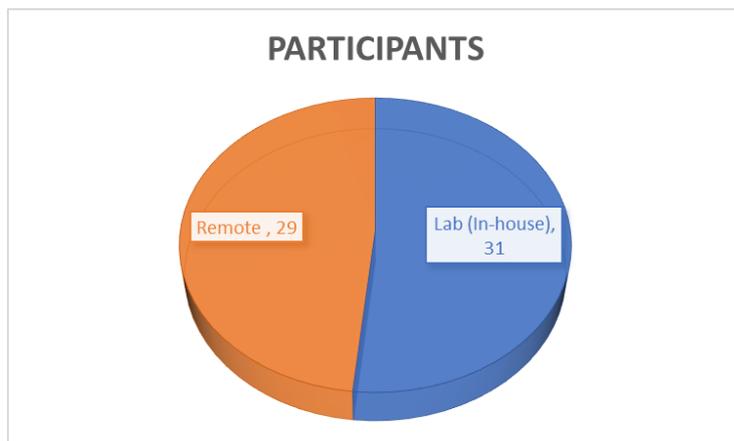
Other participants data such as income and employment were exempted from the study as there was lack of literary support (content validity) to indicate they will have a direct influence on the independent variables.

3.14 INTERNAL CONSISTENCY OF THE THESIS

The study mainly comprised 60 respondents where 31 Participants undertook the test in a Laboratory setting whilst 29 did so remotely via a freelance website (www.peopleperhour.com)

Figure 20 Lab vs Remote

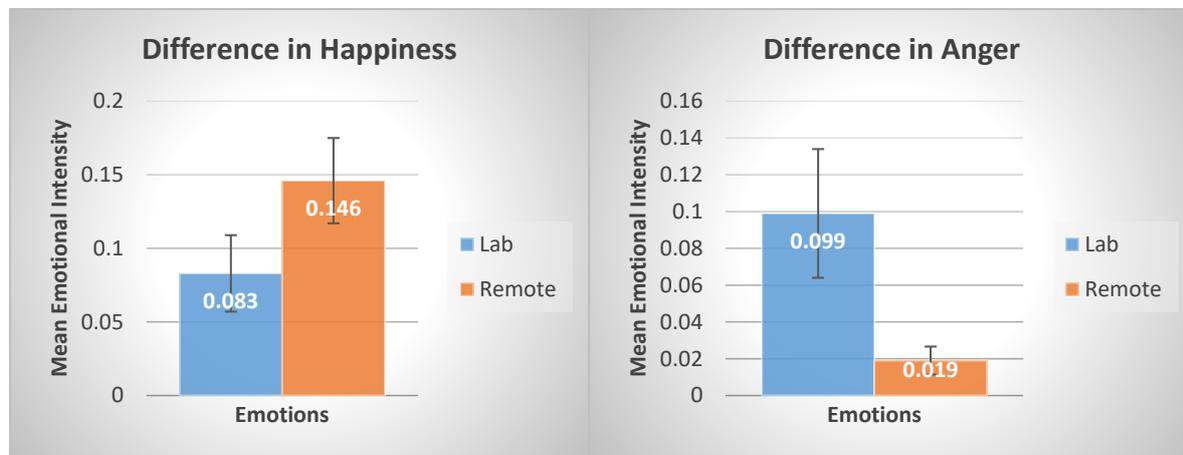
It was thus imperative to evaluate the internal consistency to understand if there are any



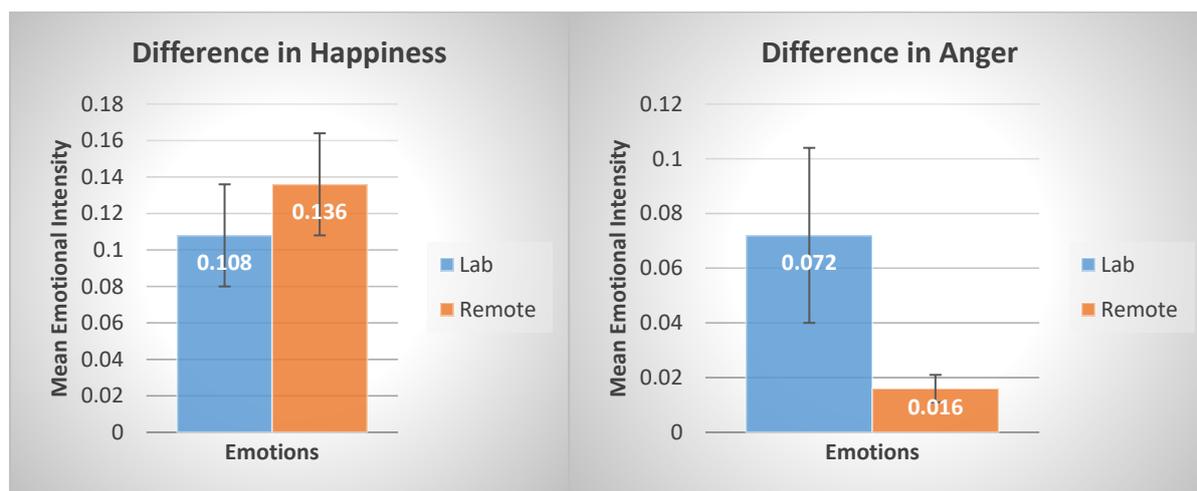
Differences between the two different set of groups in relation to the emotional responses they will elicit. Significantly, a hypothetical unpaired t-test was done to see if there was a significant difference in the emotional elements of **happiness** and **anger (bi-polar emotions)** in people who took the tests using the different environment settings. The key question thus was to unearth if there was any variation in happiness and anger among participants when they took the tests in their respective conditions. The tests indicated the following:

Figure 20a Lab vs Remote Variation

VIRAL VIDEO 1



VIRAL VIDEO 2



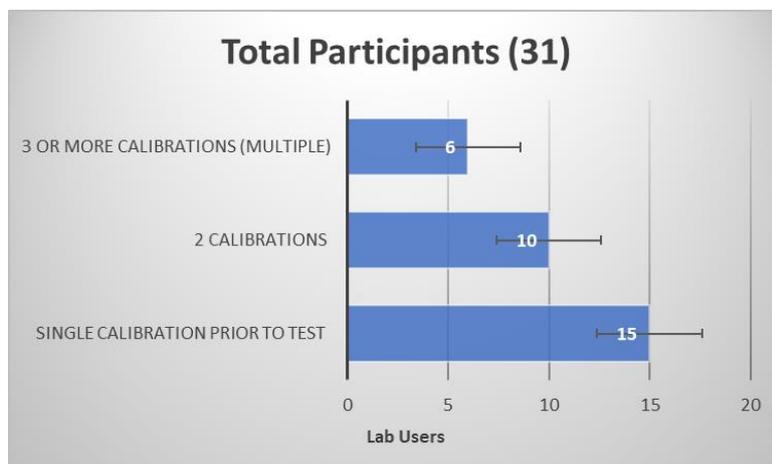
RESULTS

	Video 1	Video 2
Happiness	t(58)= 1.6,P= 0.1150	t(56)=0.6937,P=0.4907
Anger	t(58)= 2.1428,P= 0.0363	t(56)=1.666,P=0.1021

The results depicted in the graph depict that participants were happier taking the tests remotely even though the difference was not so significant. This contrasts with existing theory that stipulates that tasks with very tight experimental control (e.g., directed facial actions, which give the experimenter precise control of which emotion is displayed on the face and when) are not very characteristic of the ways in which emotions usually occur (Levenson, 2003). Conversely, it is also noticeable from the above chart that the participants

who studied under the lab conditions consistently elicited negative emotions (i.e anger) in contrast to those who did the task in a remote setting. To place the explanation into context , Lab users in the controlled environment had to go through an additional facial calibration phase before the experiment was run which in contrast the remote users were exempted from due to the inability to calibrate participants remotely. The calibration phase ensured that the facial muscles of the participants were captured by the FaceReader and the environment setting (e.g. lightening) was appropriate before the actual testing process began. This pre-requisite was done to help avert any encoding errors which will occur during the data summation process. Approximately, 1 out of 2 participants were either calibrated twice or multiple times until the calibration was successful (see figure 21 below) thereby affecting the general mood of the participants which was depicted in the verbal and non-verbal cues : (e.g. “One participant lamented that the technology just doesn’t like her” and “another participant claimed the technology was racist since the technology could not find his face”). Based on the data below it can be postulated that having to take the test more than once had an effect on the general mood of the participants which in turn also affected the emotions elicited during the test process.

Figure 21 Lab Calibrations



As much as there was evidence in emotional variations between the two different test environments it did not lead to different behaviour as participants were able to follow the needed instructions to take the test which is consistent with research involving lab and remote testing (Tulis et al.,2004).

3.15 REPLICABILITY AND GENERALISABILITY OF THE THESIS

Replicability refers to the ability of a researcher to duplicate the results of a prior study if the same procedures are followed but new data are collected (Rovenpor and Gonzales, 2015). This research study should be deemed replicable as clear guidelines for the research are provided, as well as the availability of raw data and complete statistical tests for comparative analysis. Nevertheless, it is important to assess if whether a replication of this study may suffer either from procedural or methodological differences (e.g., sample, location (remote vs lab) and materials used) when compared with the original study. A research finding may be entirely valid in one setting but not in another. Generalisability describes the extent to which research findings can be applied to settings other than that in which they were originally tested. A study is externally valid if it describes the true state outside its own setting (Oates, 2006). Shuttleworth and Wilson (2008) explain that in order to generalise the research needs to consider the representativeness, time and size.

Representativeness: In order to enhance representation, the research used two main categories of respondents which were further sub-divided as seen in the table below. The sub-categories were chosen to accurately capture the variation in the broader population.

TABLE 6 **Demographics**

Main Category	Football and Non – Football Fans
Sub- Categories	Gender
	Age
	Ethnicity

Time: The issue of **time effects** is not applicable to this research as it made no difference to the outcome of the results or directly affected the dependent variables.

Sample Size: For a priori test or comparative study a significant sample size of 60 participants was used in relation to Berger (2011) which used 40 participants in a similar study undertaken to elicit emotions from participants. The use of stratified simple random sampling was adopted for remote participants on People Per Hour (PPH) who were selected after submitting their bid to undertake the study.

3.16.1 MIXED RECRUITMENT ARRANGEMENTS

Recruitment is the dialogue which takes place between a researcher and a potential participant prior to the initiation of the consent process. It begins with the identification, targeting and enlistment of participants (volunteer patients or controls) for a research study. Patel, Doku and Tennakoon (2003) noted that recruitment involves providing information to the potential participants and generating their interest in the proposed study. Recruitment is the dialogue which takes place between a researcher and a potential participant prior to the initiation of the consent process. It begins with the identification, targeting and enlistment of participants (volunteer patients or controls) for a research study. Patel, Doku and Tennakoon (2003) noted that recruitment involves providing information to the potential participants and generating their interest in the proposed study. There are two main goals of recruitment: to recruit a sample that adequately represents the target population; to recruit sufficient participants to meet the sample size and power requirements of the study (Hulley et al, 2001; Keith, 2001). Due to the fact that this research utilised mixed environments (i.e laboratory and remote) choosing of participants for both environments differed. Participants that were chosen to undertake the study in the lab were solicited via two methods – Email and Word of Mouth (WoM). Directed emails with a participation information sheet attached to have a prior understanding of what the research will entail were sent to students within the university with clear instructions on the day, time and exact place where the research will take place. Time slots were provided to ensure that there were no clashes and that the participants will be available to undertake the study. Those who were solicited via word of Mouth were invited or spoken to directly and available time slots were arranged to meet with both the researchers schedules and that of the participants taking into consideration. Patel, Doku and Tennakoon (2003) explained that during recruitment, the sampling process can suffer from associated problems of non-response and the resultant selection bias. The proportion of eligible participants who agree to enter the study (the response rate) influences the validity of the inference that the sample represents the population of interest (Oats,2006). People who are difficult to reach and those who refuse to participate once they have been contacted tend to be different from people who do not enrol. As in most studies some people who were solicited to undertake the study did not respond to the email whilst some declined with some unsure of how their video recorded data will be kept afterwards and discarded. Some

participants also who were contacted directly refused, one particular participants claimed “he felt uncomfortable being recorded and hence offered only to do the questionnaire part of the research and leave the part that uses the FaceReader technology”. Patel, Doku and Tennakoon (2003) explicated that in some instances participants could be approached a second or third time as required until the response is achieved. This research, however, did not “push” the participants if they did not oblige to be part of the research process in the first instance as the ethics checklist provided prior to the start of the test clearly depicted that the participants should not be coerced and must be willing participants.

The participants who undertook the research remotely were derived using the online Freelance Platform (People Per Hour or www.peopleperhour.com) . There were numerous other online freelance outlets that were considered (e.g. freelancer.co.uk and truelancer.com) however, PeoplePerHour.com was chosen due to the familiarity of the platform , generalisability and representativeness of the participants that it provided. The researcher had used the platform on many occasions prior and was thus, knowledgeable on how to use the platform with regards to posting a project , searching and bidding for a project and accepting projects. The advantage of knowing the afore mentioned saved ample time to learn how to use the platform. Secondly, the participants groups that were selected were targeted to fill a quota based on Location (UK audience, Europe and rest of the World) , Gender and Age. Due to the global reach of the platform it offered a varied demographic of participants who applied to undertake the research study and subsequently were pre-screened based on the aforementioned criteria to fill the quota needed for representativeness and generalisability. It is often assumed that video recording which is done remotely using a software of choice will have an impact on participants and their behaviour but Heath, Hindmarsh and Luff (2010) suggested taking an empirical approach to the question and examining the data itself to see whether there is any evidence of behaviour orienting to the camera.

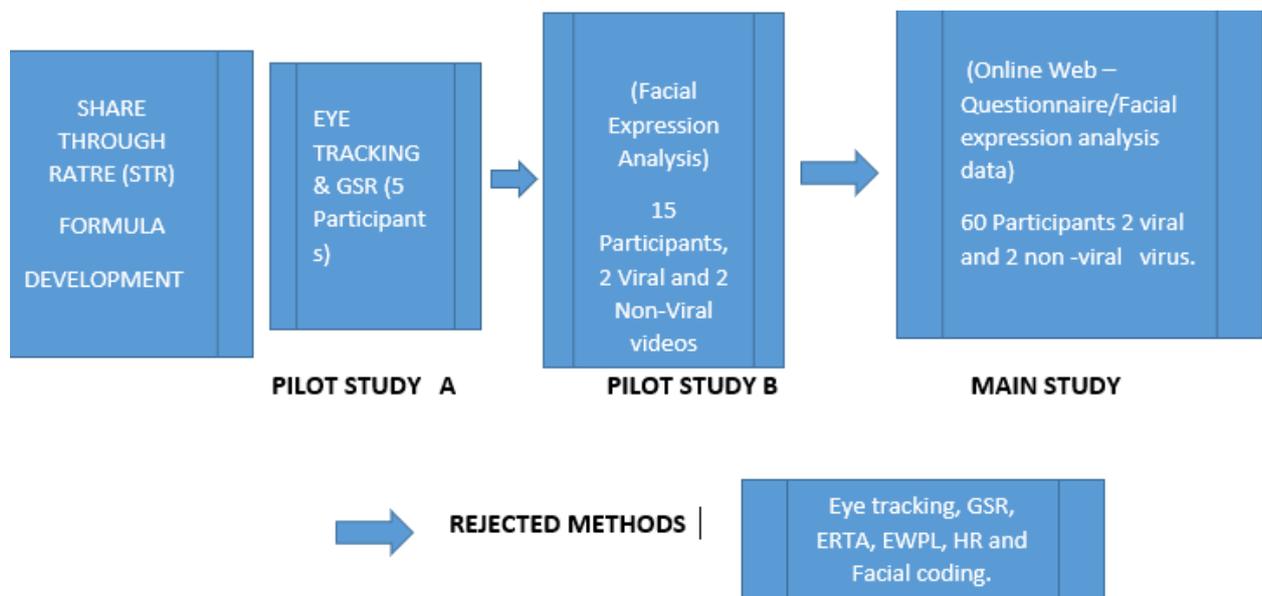
3.16.2 MIXED ENVIRONMENTS

Dray and Siegel (2004) explained that one key advantage of lab testing in contrast to remote testing is that the facilitator or researcher can accurately judge non-verbal and paraverbal cues (body language , tone of voice and non-verbal sounds) which was significantly noted in

the lab experiment. Hence, it was noted from the study that users that had participated in the lab had shown more anger (via body language , tone of voice and non-verbal sounds and data collated from the FaceReader) as compared to those who did the tasks remotely. The research noted that the negative emotions cues could be attributed to the negative mood that was seen in test subjects that have had to calibrate their face more than once before they undertook the main test. Ultimately, the key question then is should the researcher ideally opt to undertake any calibration prior to the start of the test to offset any negative effect on the actual test which could originate from negative mood? The answer is that the researcher should evaluate the drawbacks of the research from both angles: if the researcher decides to omit any calibration there is a higher probability that the actual test could lead to a lot of participants data rejected due to poor encoding in real time whilst undertaking the calibration will significantly result in reducing poor encoded data. Hence, this research opted to calibrate participants who did the test in house (lab).

Significantly, It was evident from the data analysis that some participants who undertook the thesis remotely had some of the data rejected for some videos as their face could not be calibrated to extract any emotional data. Conversely, remote participants mood will not have been affected by pre-test calibration procedures. More so, Dray and Siegel (2004) observed that some key advantages of remote testing is freedom from facilities and time saving. This is accurate to a degree as the study using the lab had to have had certain procedures and tools in place to ensure that it was implementable. For e.g. the lightening had to be on and bright enough, the web cam had to be working and be able to capture the participants face and most importantly the Wi-Fi network had to be working without any network interruption. Any of these had the potential to abrupt the study unlike in the remote setting where if any of the problems did occur there was sufficient time to pause the study and continue in a later time or to rectify using an alternate technology.

3.17 THESIS RESEARCH JOURNEY



Pilot study A - was the first step to understand the most effective way for encapsulating the theories and to test if emotions can be measured using either Eye Tracking or the Galvanic Skin Response. The methods were rejected on the basis that Eye Tracking is primarily used to measure the attention of a participant whilst the GSR is used to measure arousal in humans and not emotions. Thus, it was important to find a method that exactly measures emotions when a participant is exposed to a video stimulus. Previous studies such as (Berger and Milkman, 2012; Danner et al., 2014) had used a questionnaire survey and facial expression recognition software thus it was found prudent to emulate and incorporate the methods in unison.

Pilot Study B - 15 participants (9 Football Fans and 6 Non – Football Fans) were first used to undertake the research study which was used to assess the practicality and the possibility to deduce and analyse data from the corresponding study. The pilot study used 2 viral videos and 2 non-viral videos. The results of the pilot study which showed the emotional variations between football fans and non – football fans were subsequently published in a reputable digital marketing publication called **SemRush** (<https://www.semrush.com/blog/going-viral-which-of-the-six-emotions-make-video-content-go-viral/>).

Main Study - The research was scaled up to 60 participants (32 football fans and 28 non-football fans) comprising 2 viral and 2 non-viral videos. Data gathered from the research achieved the following 1) Assessed the validity of the facial expression analysis recognition

software in comparison with the self-measured report (i.e questionnaire survey) 2) Measured and analysed the mean emotional intensities of the participants (football fans and non-football fans) 3) Measured and analysed the likelihood to share viral videos 4) Discovered the phenomenon of emotional shifts and emotional triggers in line with the objectives of the research.

3.18 ETHICAL CONSIDERATIONS OF THE THESIS

The Ethics issue is important as this study relied heavily on human participants to obtain quantitative data. The rights of the participants as identified by both (Oates, 2006; Saunders, Lewis and Thornhill, 2009) comprised the following in the study:

The right to not participate: Participants who did not wish to participate in the study were not compelled to.

Right to withdraw: Participants had the right to withdraw from the study at any time, even after the study has been done. Data related to the participant(s) will be excluded from the research and destroyed. Participants may also be asked to withdraw if certain peculiar circumstances will affect the research. For e.g., participants who were camera shy or did not like being recorded.

Right to give informed consent: Participants were encouraged to give their consent only after receiving complete information regarding the purpose of the research, why it is being undertaken, and benefits expected from it. They were also privy to who was undertaking the research, what was involved, whether they will receive any incentives, and how the data will be used.

Right to anonymity: Participants in the study had the right to know that their identity and location will be protected. Where necessary in the study and the participants need to be named, pseudonyms will be used.

Right to confidentiality: Participants can opt to have their data obtained from them to remain confidential; hence, if requested, certain information or excerpts will be left out of the report findings.

4.0 ANALYSIS (RESULTS)

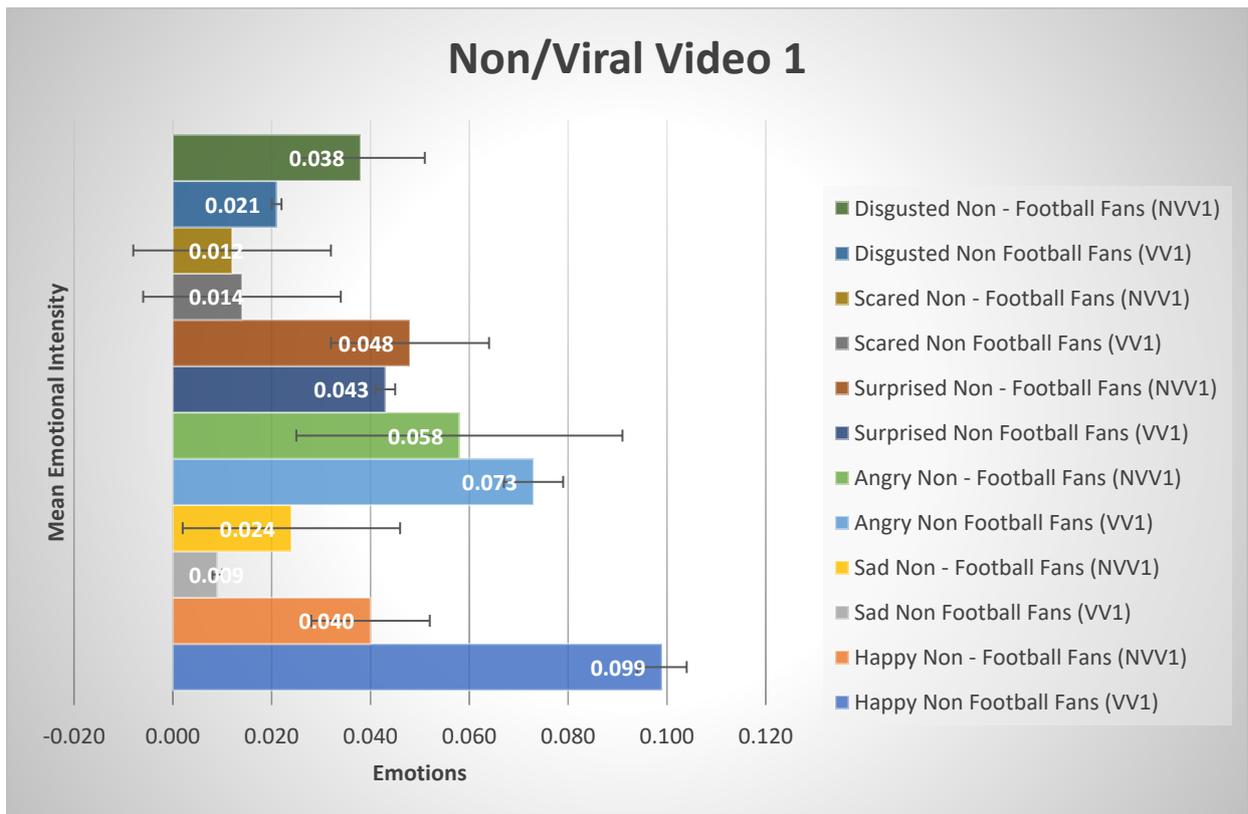
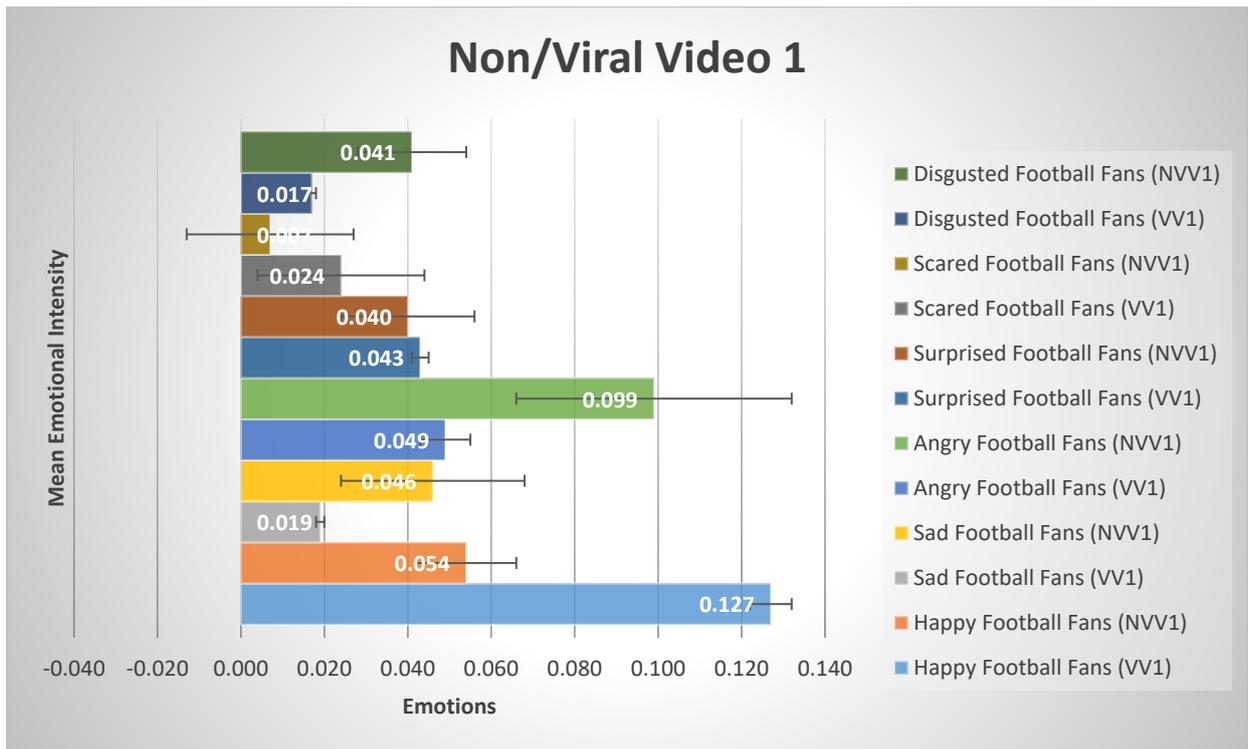
The results chapter of this thesis consists of the data that has been collected as part of the research. The analysis chapter will provide a comprehensive representation of statistical and graphical data. The analysis chapter will be divided into three segments (1, 1b and 1c,2 and 3) that meets the thesis objectives. In **results 1a**, a graphical representation of the emotional variations is provided followed by a data analysis of the corresponding hypothesis. **results 1b** takes a closer focus on the intent to share, the notion is that there are certain emotions which inherently affect sharing. **Results 1c** tends to give insight into when the intent to share occurs within a given viewed framework. An in-depth explanation and discussion of the results is provided in the subsequent chapter.

4.1 RESULTS 1a

This chapter goes to depict an analytical understanding of the differences in emotions (i.e Happiness, Surprise, Anger and Sadness) between the video groups (i.e viral and non-viral videos). The video groups are also segmented further by fan groups (football fans and non-football fans, male football fans, female football fans, male non-football fans and female non-football fans) to provide a robust analytical overview of the mean variations. Based on the research design and experimental conditions an independent sample t-test (unpaired t test) was used to test for the variation in the emotional intensities on the video groups by using the Mean, SD (Standard Deviation) and N (Sample Size) derived from the data collated. *Refer to Appendix B for the exact statistical computations.*

VIDEO GROUPS VARIATION

This segment goes to provide an understanding of the differences in emotional intensity between viral video groups (i.e. Viral video 1 and Non-viral video 1)



FOOTBALL FANS

H1a: There is a significant difference in happiness between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI (Confidence Interval). The results indicate that there was a significant difference in happiness intensity between a viral video and a non-viral video viewed by football fans. **Where, $t(62) = 2.408$, $P = 0.0190$. Hence, we reject the null hypothesis.**

NON – FOOTBALL FANS

H1b: There is a significant difference in happiness between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video viewed by non-football fans. *Where, $t(53) = 1.873$, $P = 0.0665$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H2a: There is a significant difference in surprise between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the surprise intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video viewed by football fans. *Where, $t(62) = 1.832$, $P = 0.09$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

H2b: There is a significant difference in surprise between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate

that there was no significant difference in surprise intensity between a viral video and a non-viral video viewed by non-football fans. *Where, $t(53) = 0.2286, P = 0.8201$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H3a: There is a significant difference in anger between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the anger intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video viewed by football fans. *Where, $t(62) = 1.0388, P = 0.3029$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

H3b: There is a significant difference in anger between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video viewed by non-football fans. *Where, $t(53) = 0.3470, P = 0.7300$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H4a: There is a significant difference in sadness between a viral video and a non-viral video viewed by football fans.

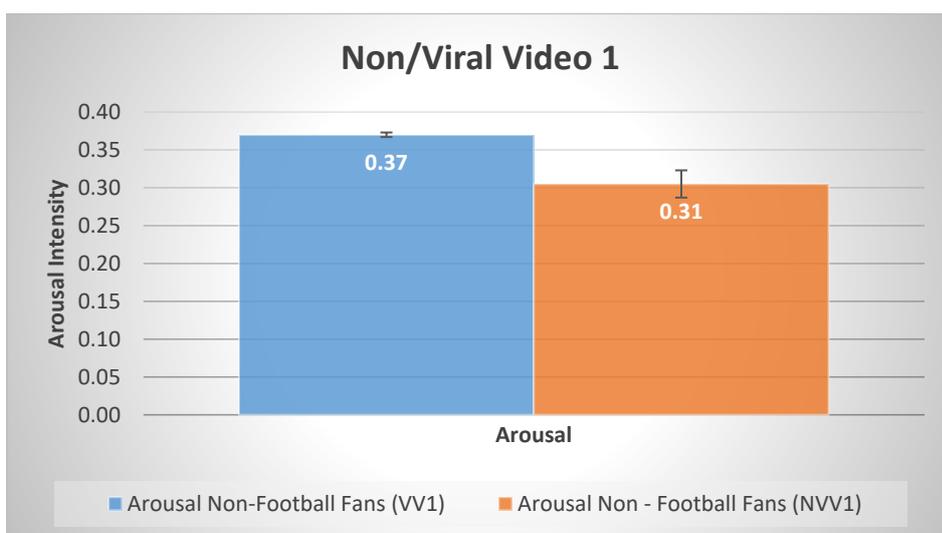
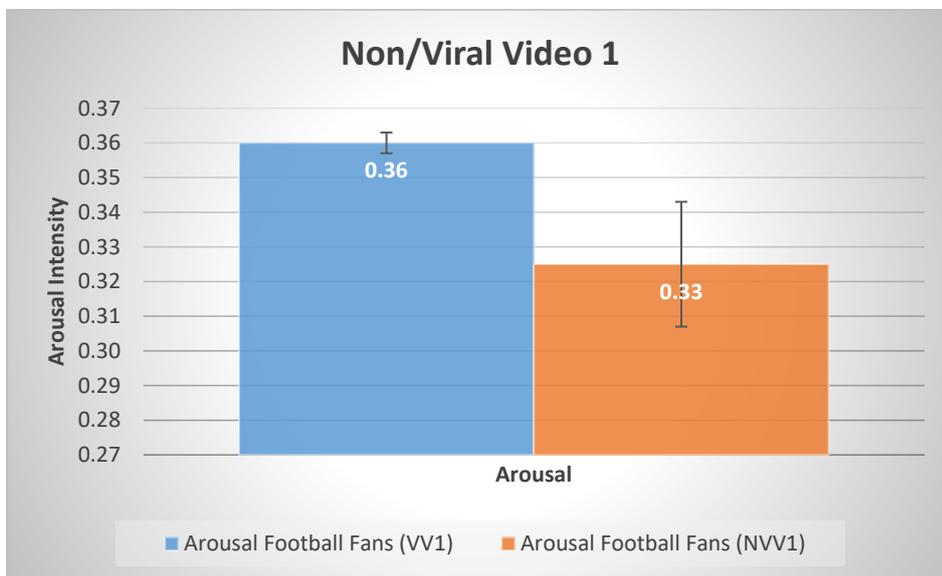
An independent samples t-test was performed to compare the sadness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by football fans. *Where, $t(62) = 1.1749, P = 0.2445$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

H4b: There is a significant difference in sadness between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the sadness intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by non-football fans. *Where, $t(53) = 0.7448, P = 0.4597$. Hence, we accept the null hypothesis.*

This segment goes to provide an understanding of the differences in arousal between viral video groups (viral video and non-viral video).



FOOTBALL FANS

H5a: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video when viewed by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non – viral video when viewed by football fans. *Where, $t(62) = 4.204, P = 0.0947$. Hence, we accept the null hypothesis.*

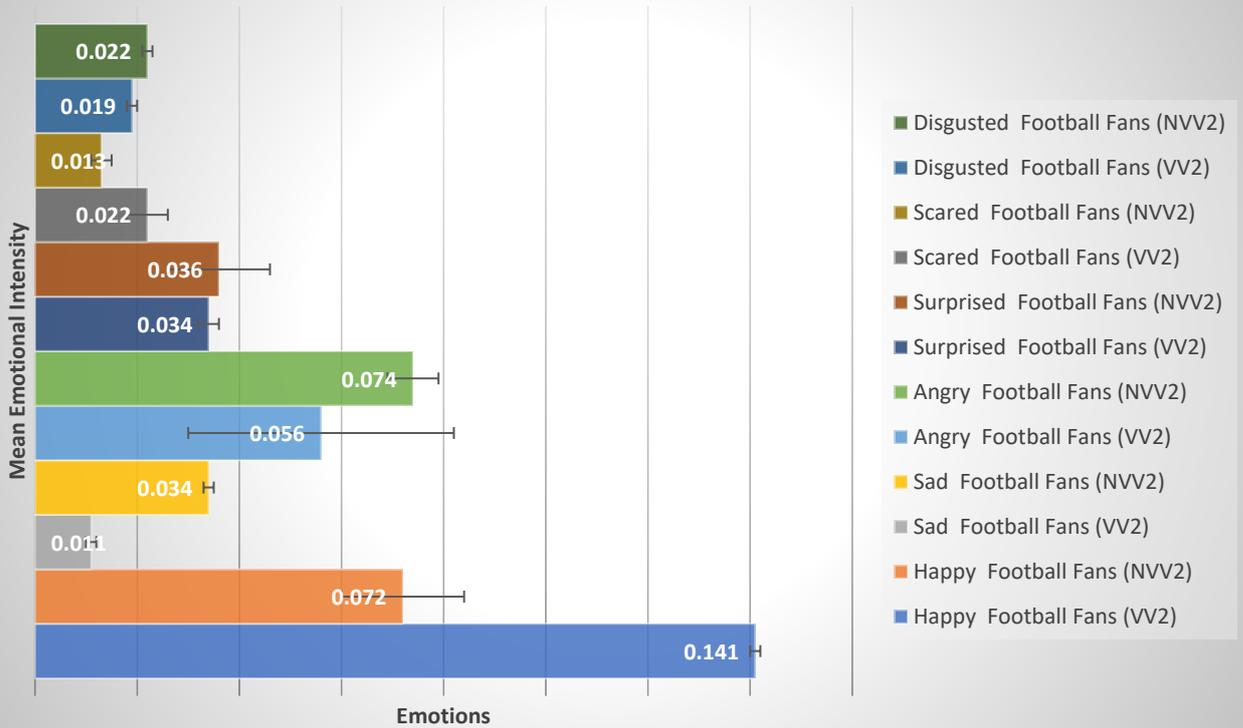
NON – FOOTBALL FANS

H5b: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by non-football fans.

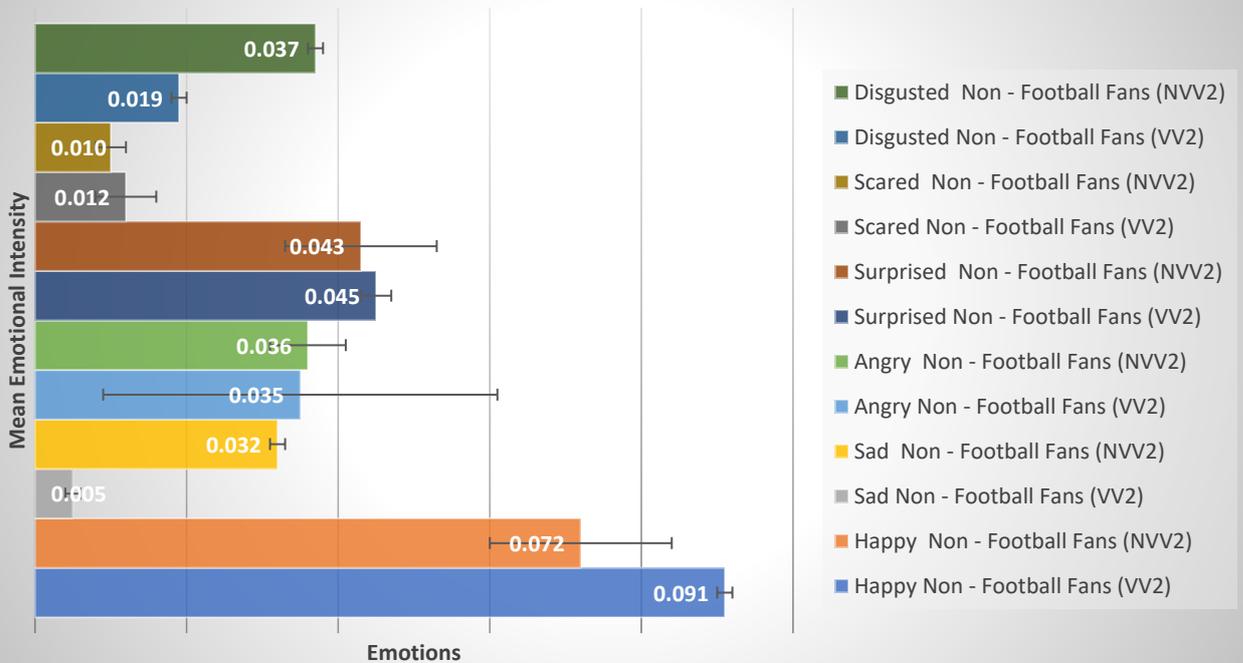
An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video when viewed by non-football fans at a 95% CI. The results indicate that there was a significant difference in arousal intensity between a viral video and a non – viral video viewed by non - football fans. **Where, $t(53) = 3.8668, P = 0.0003$. Hence, we reject the null hypothesis.**

This segment goes to provide an understanding of the differences in emotional intensity between viral video groups (i.e. Viral video 2 and non-viral video 2).

Non/Viral Video 2



Non/Viral Video 2



FOOTBALL FANS

H1a: There is a significant difference in happiness between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was a significant difference in happiness intensity between a viral video and a non-viral video when viewed by football fans. **Where, $t(61) = 2.0955$, $P = 0.0403$. Hence, we reject the null hypothesis.**

NON – FOOTBALL FANS

H1b: There is a significant difference in happiness between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by non-football fans. *Where, $t(51) = 0.6476$, $P = 0.5202$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H2a: There is a significant difference in surprise between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the surprise intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by football fans. *Where, $t(61) = 0.1318$, $P = 0.8956$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

H2b: There is a significant difference in surprise between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by non-football fans. *Where, $t(51) = 0.0696, P = 0.9448$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H3a: There is a significant difference in anger between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the anger intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by football fans. *Where, $t(61) = 0.4809, P = 0.6323$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

H3b: There is a significant difference in anger between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the anger intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by non-football fans. *Where, $t(53) = 0.3470, P = 0.7300$. Hence, we accept the null hypothesis.*

FOOTBALL FANS

H4a: There is a significant difference in sadness between a viral video and a non-viral video viewed by football fans.

An independent samples t-test was performed to compare the sadness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video

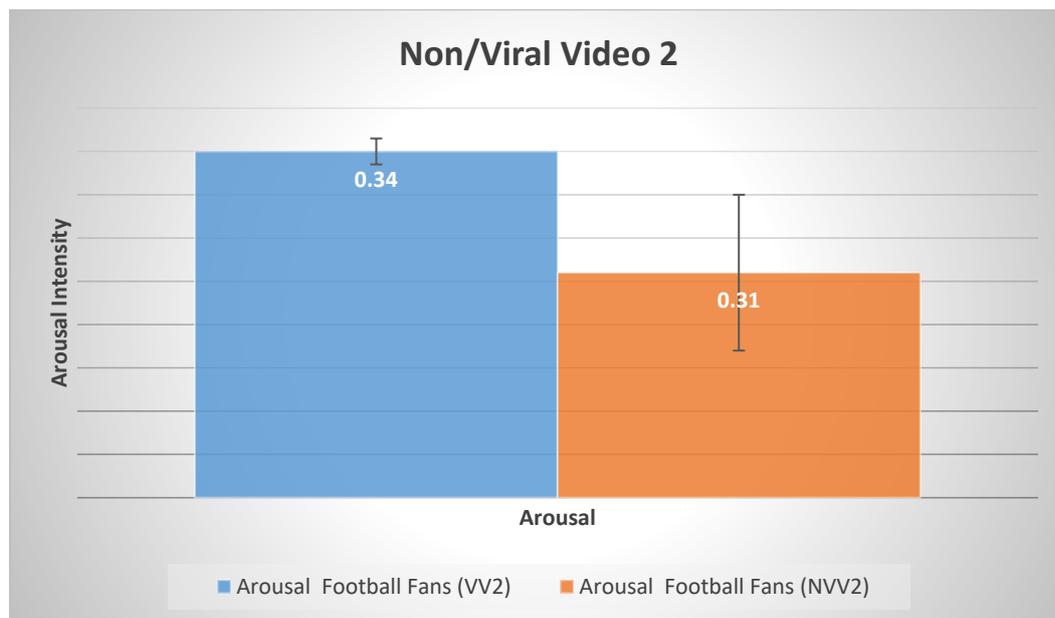
when viewed by football fans. Where, $t(61) = 1.1714$, $P=0.09$. Hence, we accept the null hypothesis.

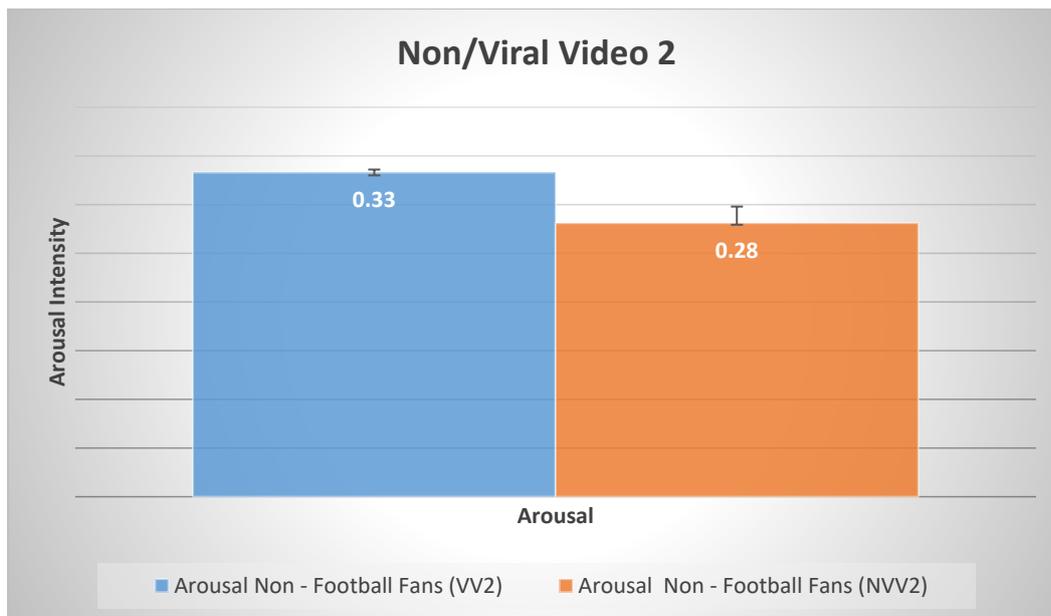
NON – FOOTBALL FANS

H4b: There is a significant difference in sadness between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the sadness intensity of non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by non-football fans. Where, $t(51) = 1.8361$, $P= 0.072$. Hence, we accept the null hypothesis.

This segment goes to provide an understanding of the differences in arousal between viral video groups (viral video and non-viral video).





FOOTBALL FANS

H5a: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by football fans.

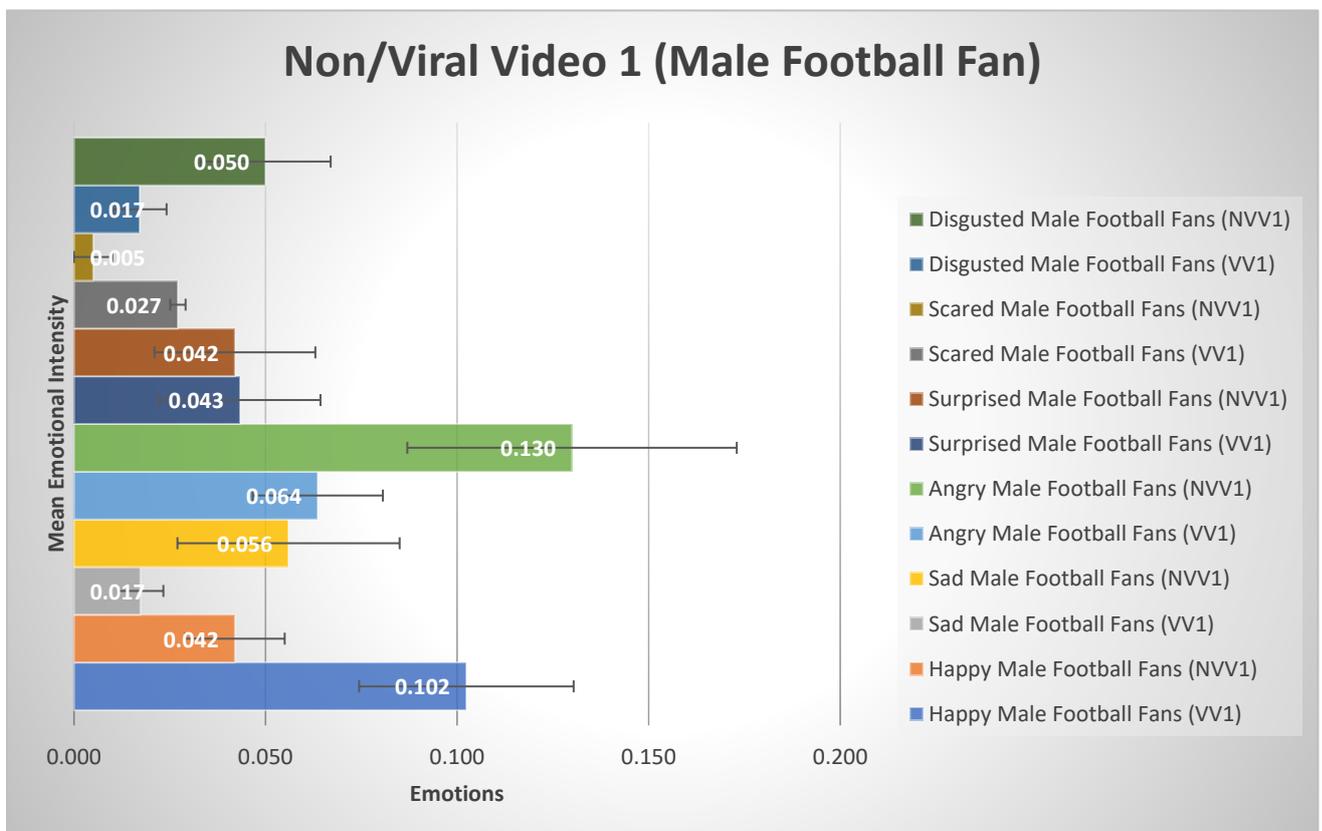
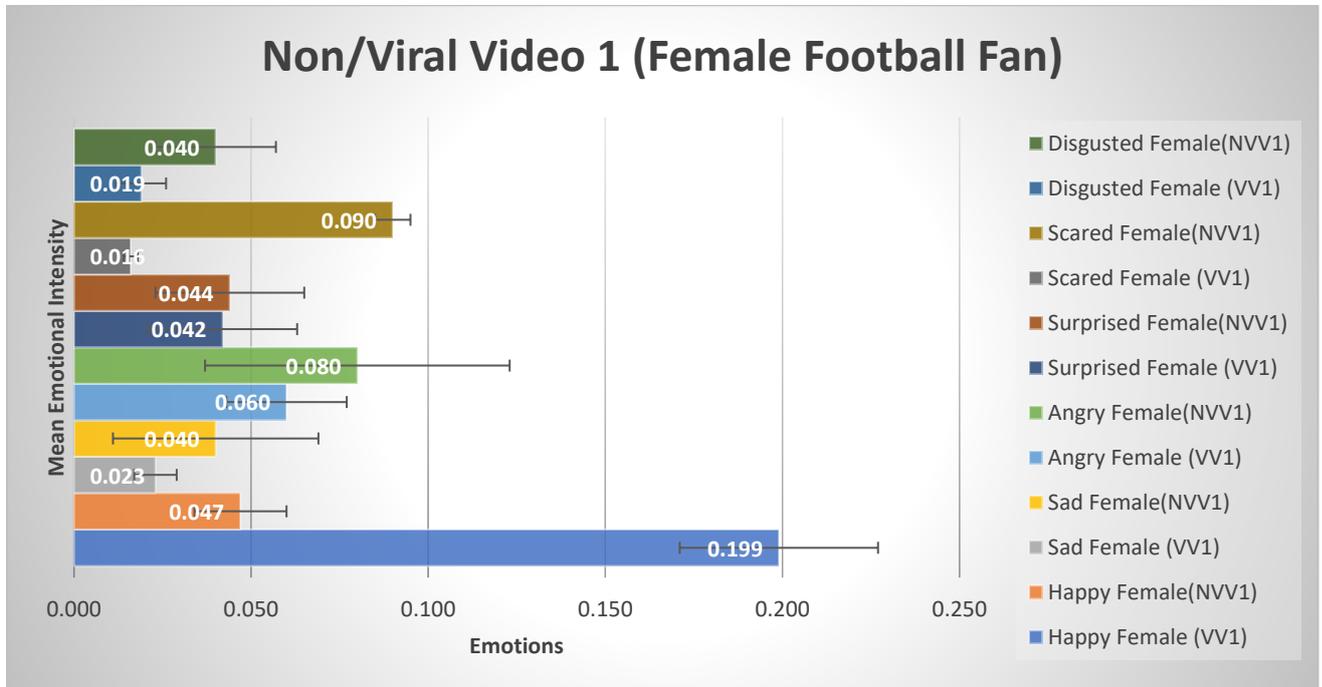
An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non – viral video when viewed by football fans. *Where, $t(61) = 0.7368$, $P = 0.4641$. Hence, we accept the null hypothesis.*

NON – FOOTBALL FANS

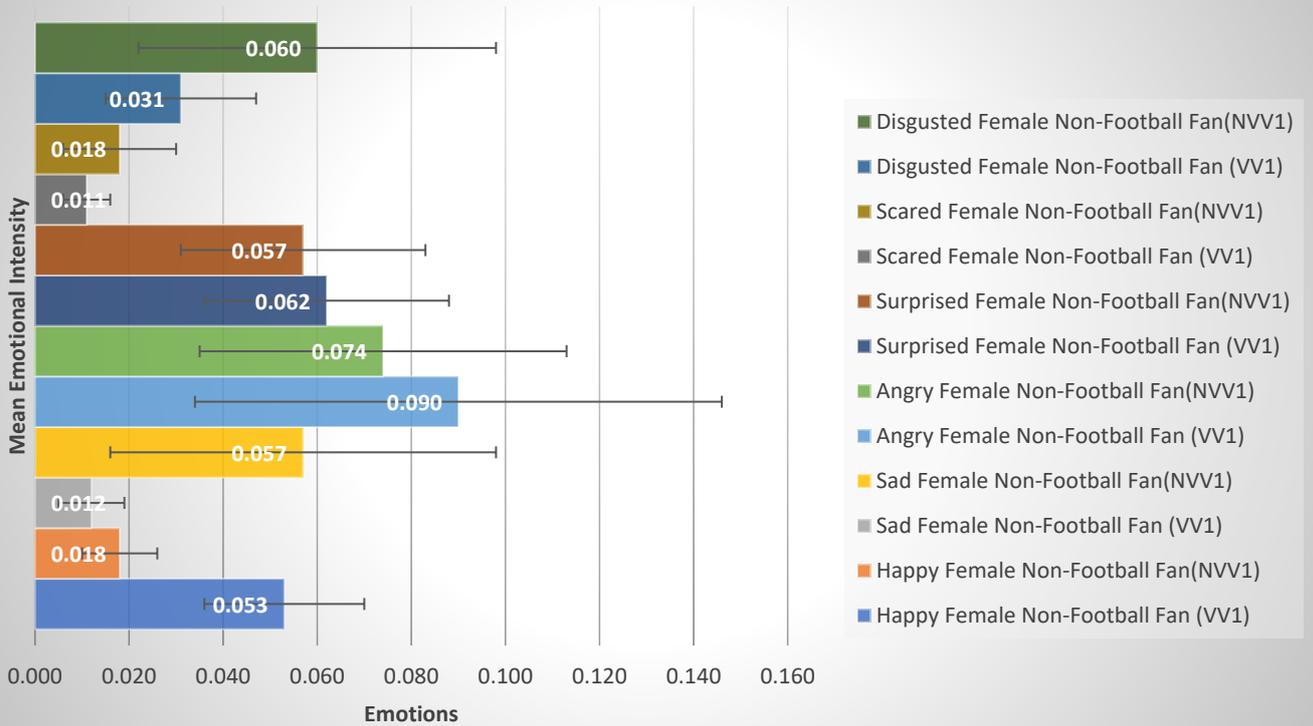
H5b: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by non-football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by football fans at a 95% CI. The results indicate that there was a significant difference in arousal intensity between a viral video and a non – viral video viewed by non-football fans. **Where, $t(51) = 2.2625$, $P = 0.028$. Hence, we reject the null hypothesis.**

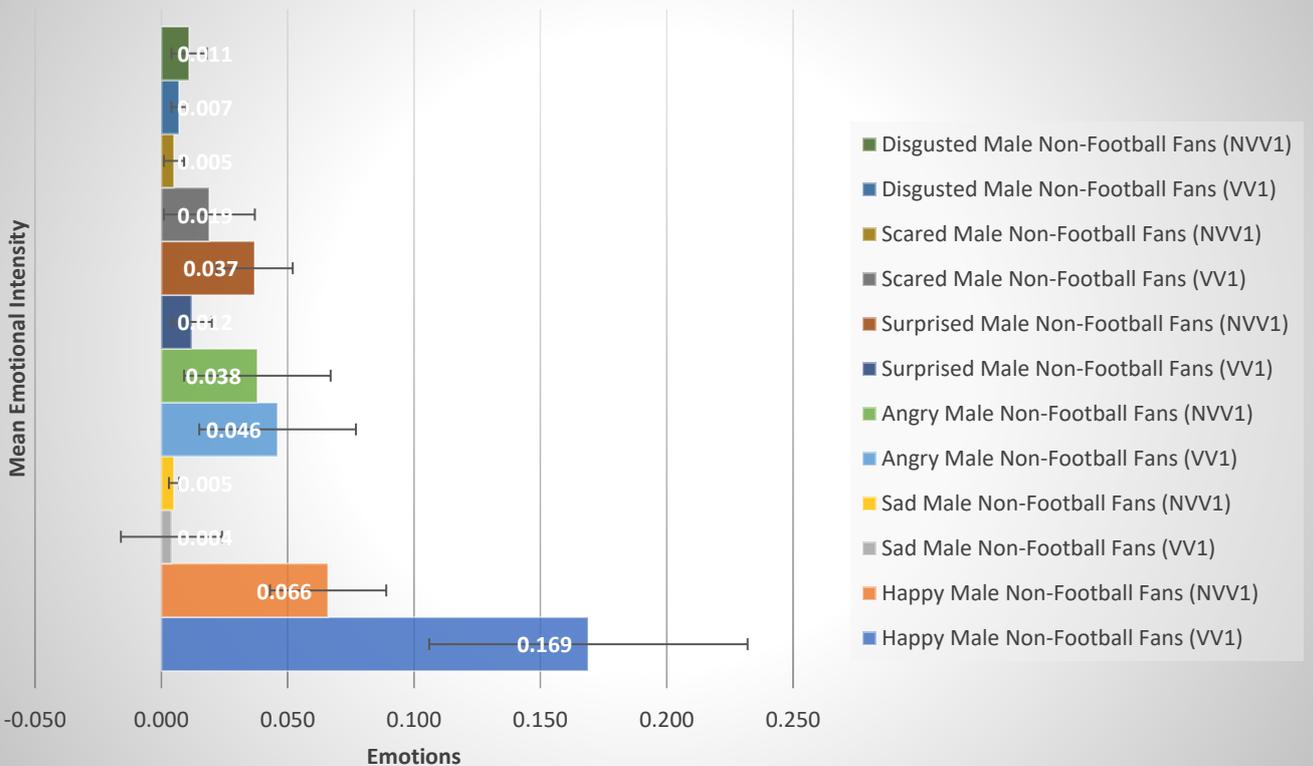
This segment goes to provide an understanding of the differences in emotional intensity between viral video groups (i.e. Viral video 1 and non-viral video 1) segmented by male football fans, female football fans and male non-football fans and female non-football fans.



Non/Viral Video 1 (Female Non-Football Fans)



Non/Viral Video 1 (Male Non-Football Fans)



VIRAL VIDEO 1

H1a: There is a significant difference in happiness between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(46) = 1.6966, P = 0.0965$. Hence, we accept the null hypothesis.*

H1b: There is a significant difference in happiness between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was a significant difference in happiness intensity between a viral video and a non-viral video when viewed by female football fans. **Where, $t(12) = 2.9658, P = 0.0118$. Hence, we reject the null hypothesis.**

H1c: There is a significant difference in happiness between a viral video and a non-viral video viewed by male non-football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by male non-football fans. *Where, $t(20) = 1.5296, P = 0.1418$. Hence, we accept the null hypothesis.*

H1d: There is a significant difference in happiness between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(30) = 1.8570, P = 0.0743$. Hence, we accept the null hypothesis.*

H2a: There is a significant difference in surprise between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the surprise intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(46) = 0.0373, P = 0.9704$. Hence, we accept the null hypothesis.*

H2b: There is a significant difference in surprise between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the surprise intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.0201, P = 0.9843$. Hence, we accept the null hypothesis.*

H2c: There is a significant difference in surprise between a viral video and a non-viral video viewed by male non-football fans.

An independent samples t-test was performed to compare the surprise intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(20) = 1.4948, P = 0.1506$. Hence, we accept the null hypothesis.*

H2d: There is a significant difference in surprise between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the surprise intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(30) = 0.1444, P = 0.8662$. Hence, we accept the null hypothesis.*

H3a: There is a significant difference in anger between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the anger intensity of male football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(46) = 1.3719$, $P = 0.1768$. Hence, we accept the null hypothesis.*

H3b: There is a significant difference in anger between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the anger intensity of female football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.3283$, $P = 0.7484$. Hence, we accept the null hypothesis.*

H3c: There is a significant difference in anger between a viral video and a non-viral video viewed by male non- football fans.

An independent samples t-test was performed to compare the anger intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by male non- football fans. *Where, $t(20) = 1.4948$, $P = 0.1506$. Hence, we accept the null hypothesis.*

H3d: There is a significant difference in anger between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the anger intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(30) = 0.2361$, $P = 0.8151$. Hence, we accept the null hypothesis.*

H4a: There is a significant difference in sadness between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the sadness intensity of male football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(46) = 1.2933$, $P = 0.2024$. Hence, we accept the null hypothesis.*

H4b: There is a significant difference in sadness between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the sadness intensity of female football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.3769$, $P = 0.7128$. Hence, we accept the null hypothesis.*

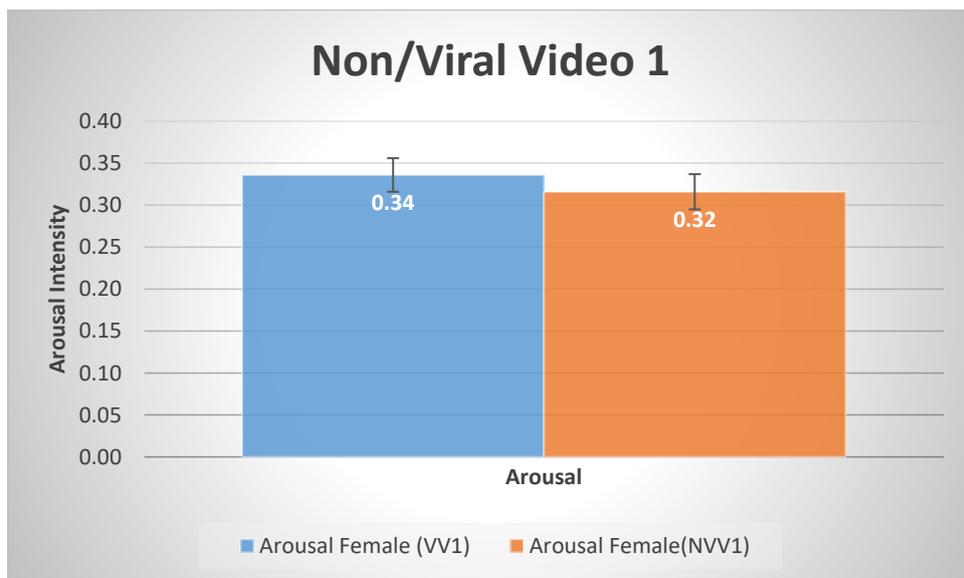
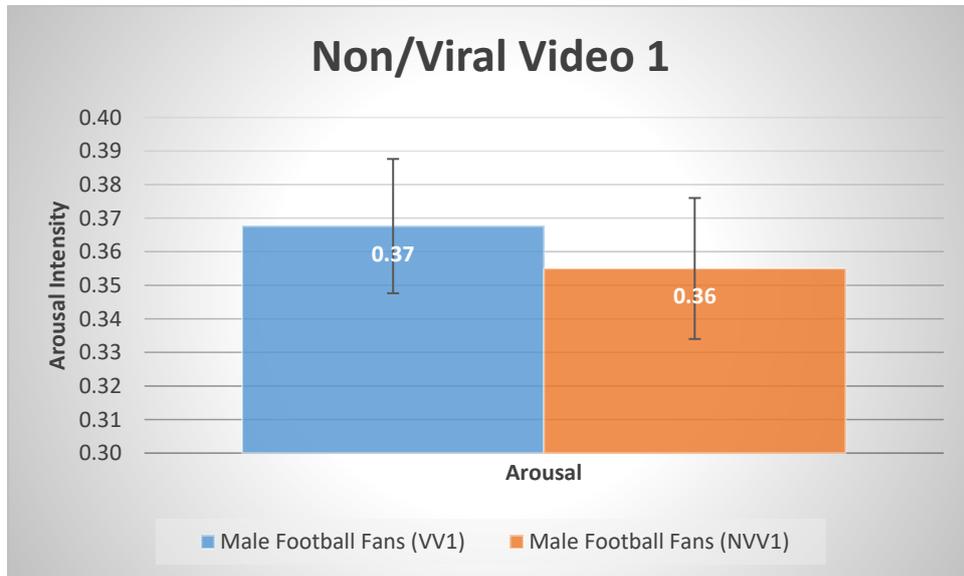
H4c: There is a significant difference in sadness between a viral video and a non-viral video viewed by male non-football fans.

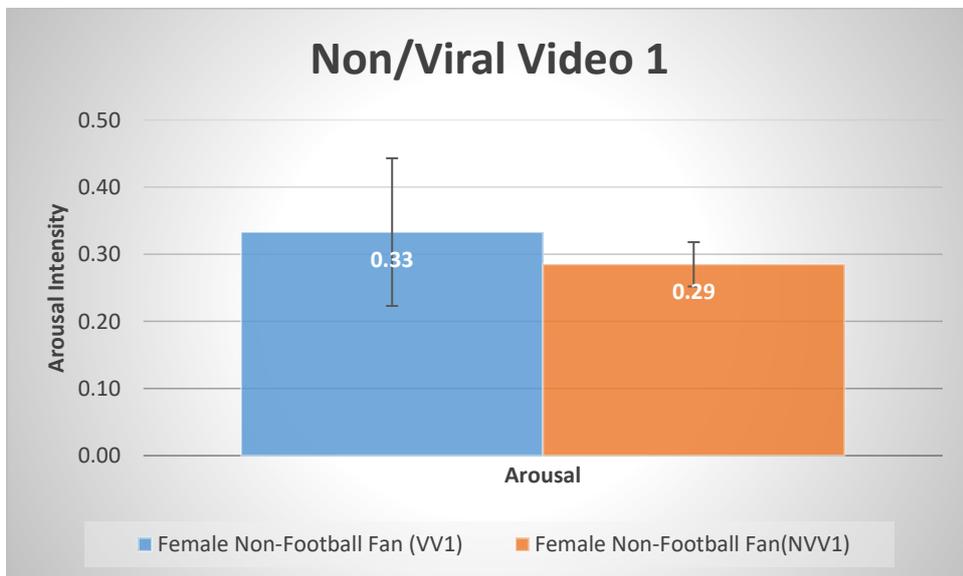
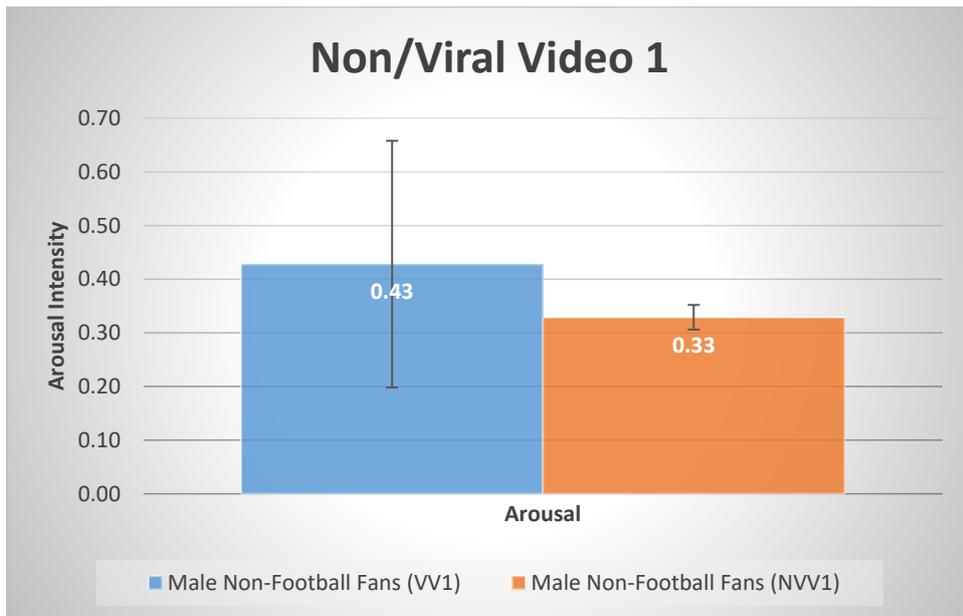
An independent samples t-test was performed to compare the sadness intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by male non-football fans. *Where, $t(20) = 0.3317$, $P = 0.7436$. Hence, we accept the null hypothesis.*

H4d: There is a significant difference in surprise between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the sadness intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(30) = 1.3448$, $P = 0.1888$. Hence, we accept the null hypothesis.*

This segment goes to provide an understanding of the differences in arousal between viral video groups (viral video and non-viral video).





H5a: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(61) = 0.3464$, $P = 0.7306$. Hence, we accept the null hypothesis.*

H5b: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.4537, P = 0.6581$. Hence, we accept the null hypothesis.*

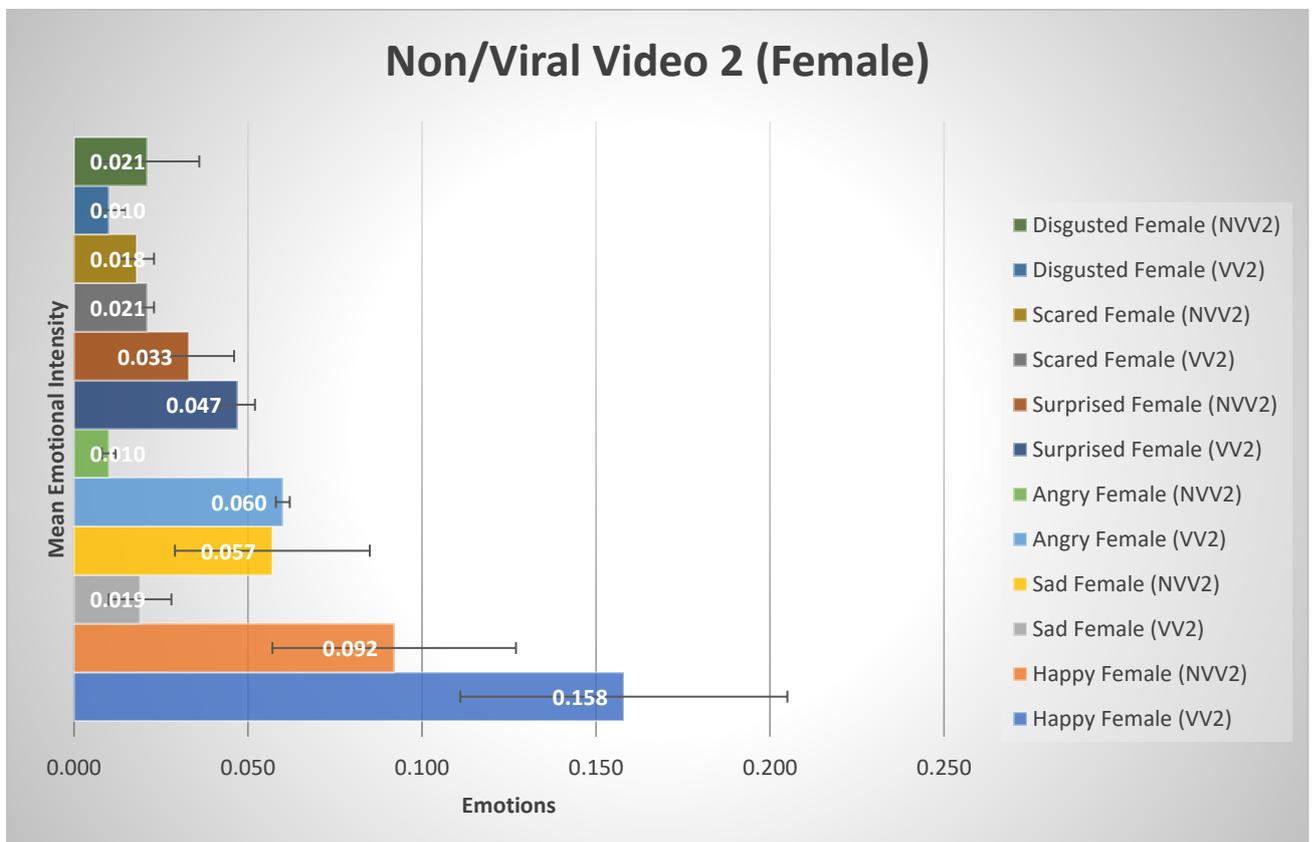
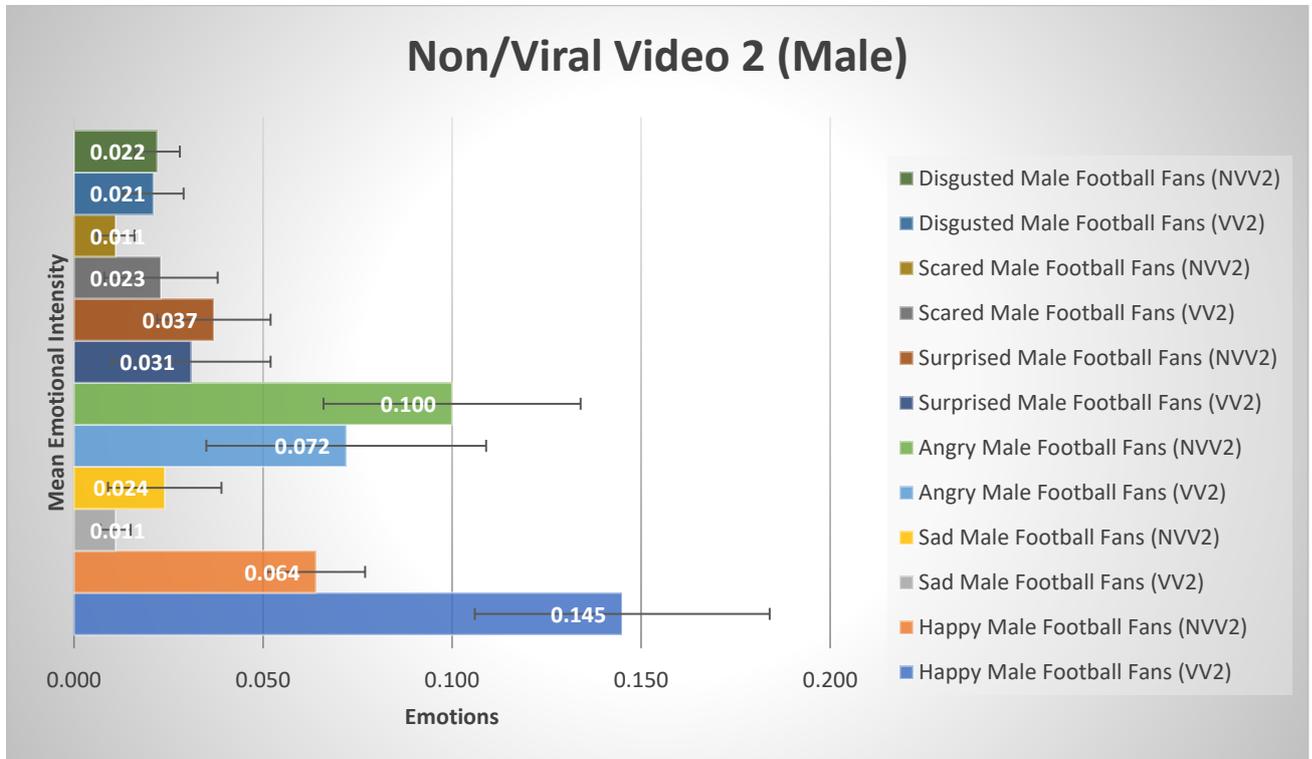
H5c: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by male non- football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by male non-football fans at a 95% CI. The results indicate that there was an extremely significant difference in arousal intensity between a viral video and a non-viral video when viewed by male non- football fans. **Where, $t(20) = 2.9315, P = 0.0083$. Hence, we reject the null hypothesis.**

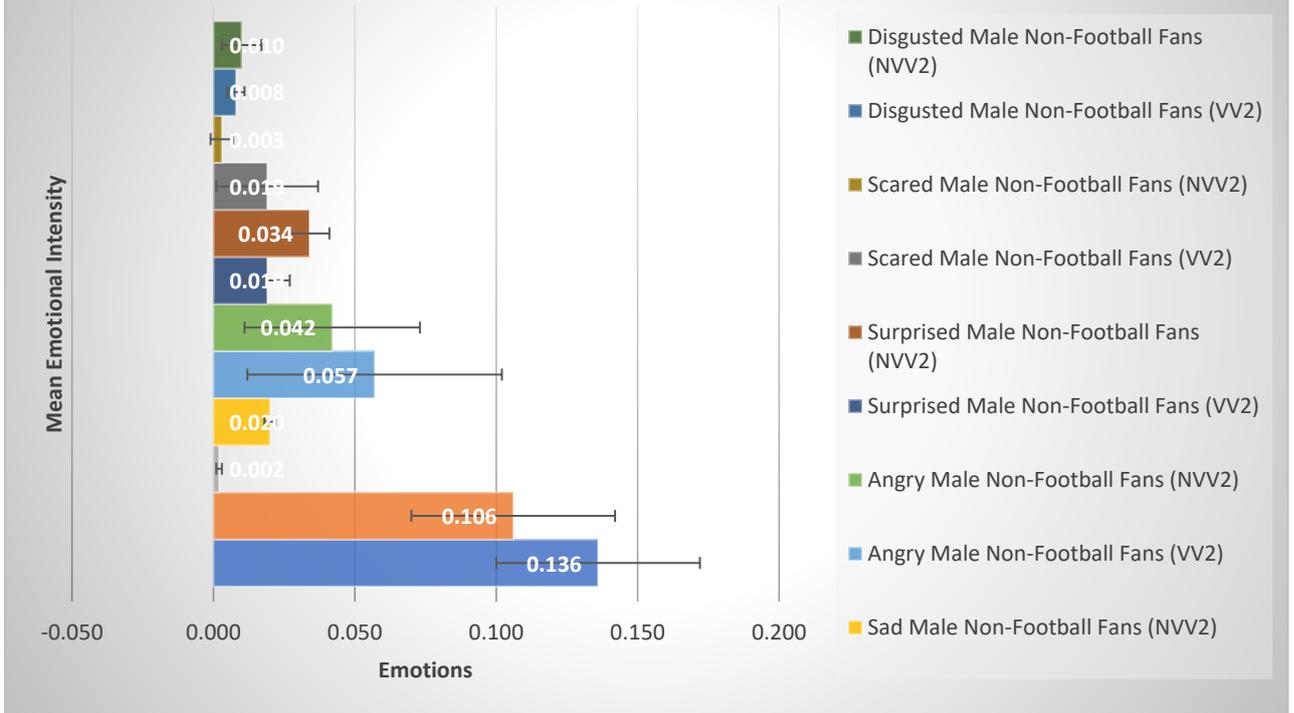
H5d: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by female non- football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by female non-football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by female non- football fans. *Where, $t(20) = 1.4005, P = 0.1716$. Hence, we accept the null hypothesis.*

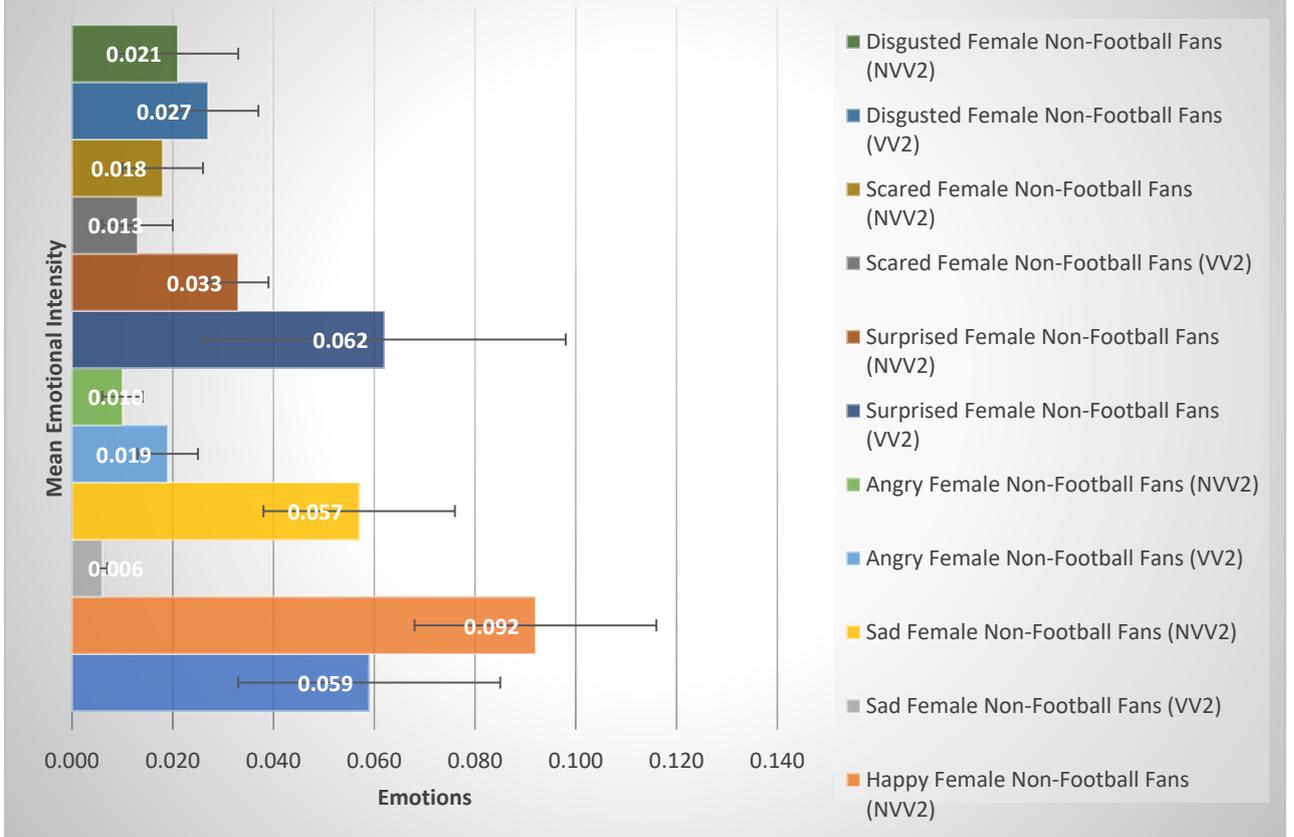
This segment goes to provide an understanding of the differences in emotional intensity between viral video groups (i.e. Viral video 2 and non-viral video 2) segmented by male football fans, female football fans and male non-football fans and female non-football fans.



Non/Viral Video 2 (Male)



Non/Viral Video 2 (Female)



H1a: There is a significant difference in happiness between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the happiness intensity of male football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(44) = 1.9345, P = 0.0595$. Hence, we accept the null hypothesis.*

H1b: There is a significant difference in happiness between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the happiness intensity of female football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 1.1251, P = 0.2826$. Hence, we accept the null hypothesis.*

H1c: There is a significant difference in happiness between a viral video and a non-viral video viewed by male non-football fans.

An independent samples t-test was performed to compare the happiness intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by male non-football fans. *Where, $t(20) = 0.5887, P = 0.5626$. Hence, we accept the null hypothesis.*

H1d: There is a significant difference in happiness between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the happiness intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in happiness intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(29) = 0.9332, P = 0.3584$. Hence, we accept the null hypothesis.*

H2a: There is a significant difference in surprise between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(44) = 0.3004, P = 0.7653$. Hence, we accept the null hypothesis.*

H2b: There is a significant difference in surprise between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.8844, P = 0.3938$. Hence, we accept the null hypothesis.*

H2c: There is a significant difference in surprise between a viral video and a non-viral video viewed by male non- football fans.

An independent samples t-test was performed to compare the happiness intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by male non- football fans. *Where, $t(20) = 0.7901, P = 0.4388$. Hence, we accept the null hypothesis.*

H2d: There is a significant difference in surprise between a viral video and a non-viral video viewed by Female non-football fans.

An independent samples t-test was performed to compare the happiness intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in surprise intensity between a viral video and a non-viral video when viewed by female non- football fans. *Where, $t(29) = 0.7700, P = 0.4475$. Hence, we accept the null hypothesis.*

H3a: There is a significant difference in anger between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the anger intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(44) = 0.5614, P = 0.5774$. Hence, we accept the null hypothesis.*

H3b: There is a significant difference in anger between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was a significant difference in anger intensity between a viral video and a non-viral video when viewed by female football fans. **Where, $t(12) = 10.4538, P = 0.001$. Hence, we reject the null hypothesis.**

H3c: There is a significant difference in anger between a viral video and a non-viral video viewed by male non-football fans.

An independent samples t-test was performed to compare the anger intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by male non-football fans. *Where, $t(20) = 0.2759, P = 0.7855$. Hence, we accept the null hypothesis.*

H3d: There is a significant difference in anger between a viral video and a non-viral video viewed by female non-football fans.

An independent samples t-test was performed to compare the anger intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in anger intensity between a viral video and a non-viral video when viewed by female non-football fans. *Where, $t(29) = 1.2635, P = 0.2165$. Hence, we accept the null hypothesis.*

H4a: There is a significant difference in sadness between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the sadness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(44) = 0.8512, P = 0.3993$. Hence, we accept the null hypothesis.*

H4b: There is a significant difference in sadness between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the sadness intensity of football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(12) = 1.2872, P = 0.2223$. Hence, we accept the null hypothesis.*

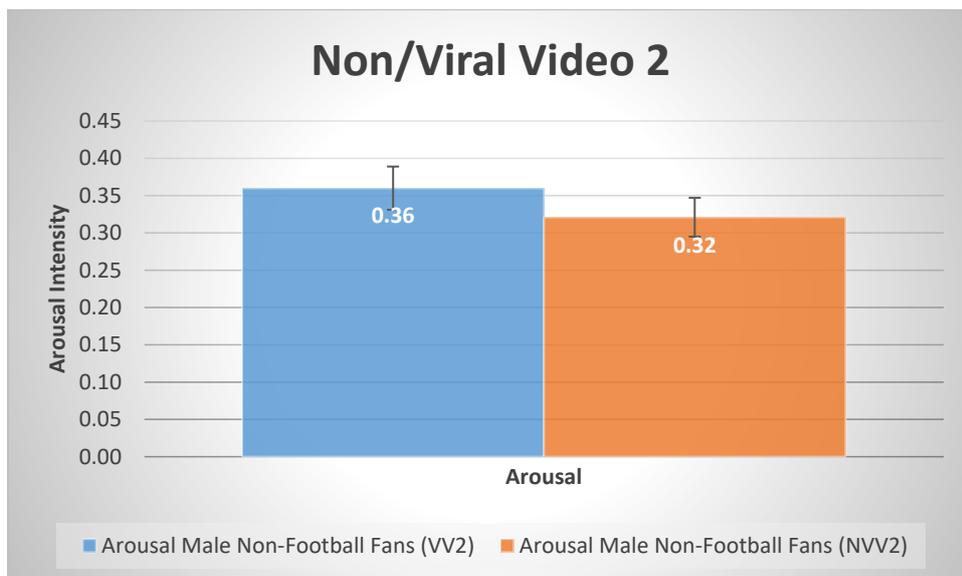
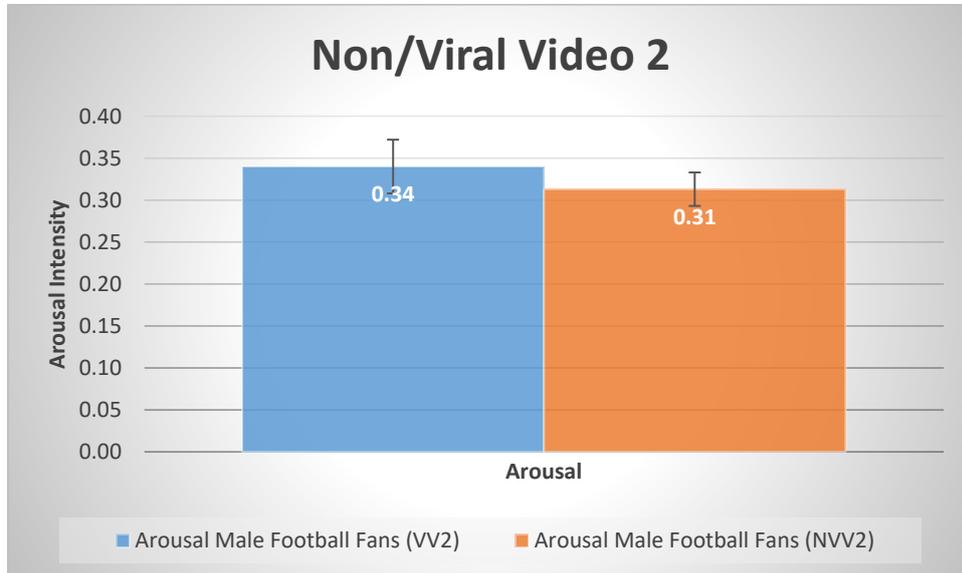
H4c: There is a significant difference in sadness between a viral video and a non-viral video viewed by male non-football fans.

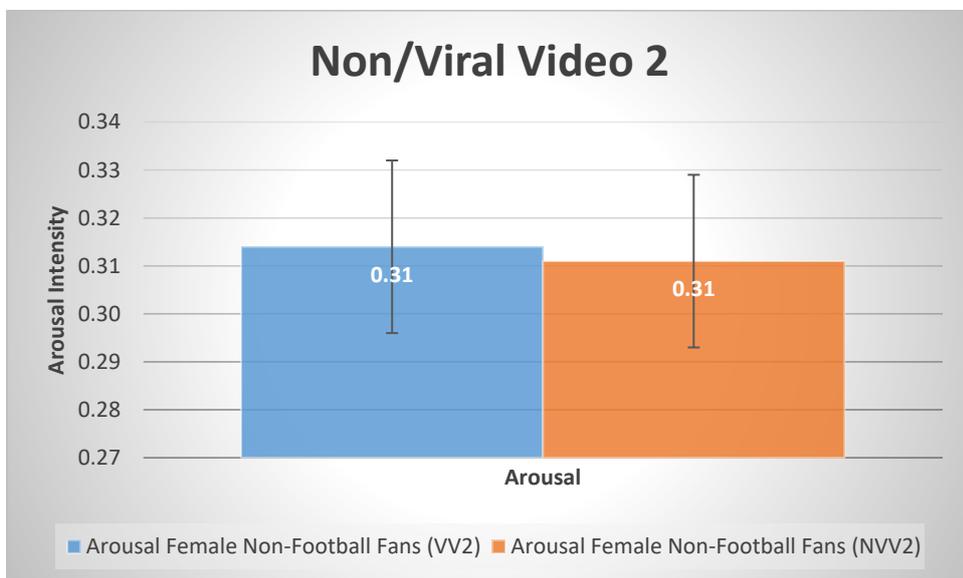
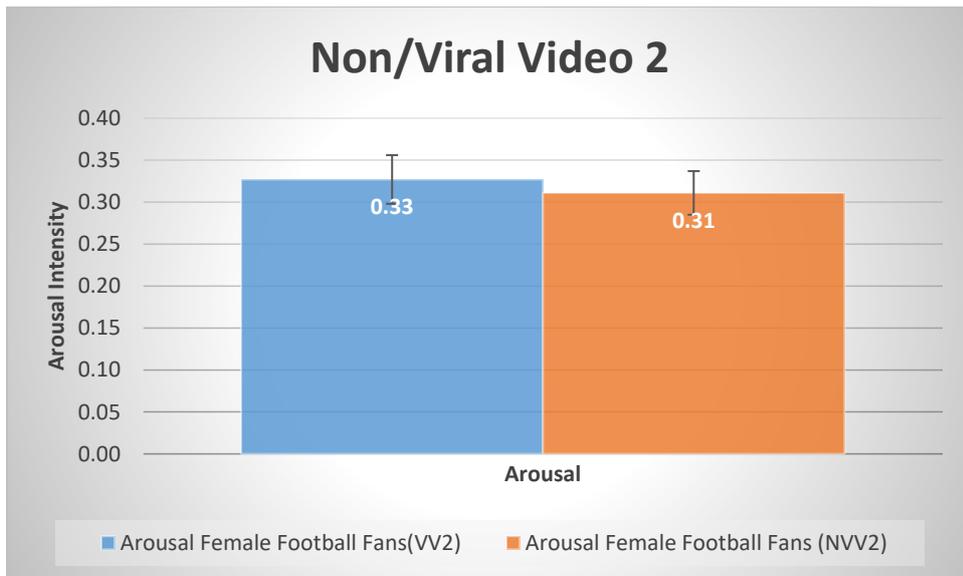
An independent samples t-test was performed to compare the happiness intensity of male non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was no significant difference in sadness intensity between a viral video and a non-viral video when viewed by male non-football fans. *Where, $t(20) = 1.1686, P = 0.2563$. Hence, we accept the null hypothesis.*

H4d: There is a significant difference in sadness between a viral video and a non-viral video viewed by Female non-football fans.

An independent samples t-test was performed to compare the sadness intensity of female non-football fans who watched a viral video and a non-viral video at 95% CI. The results indicate that there was a significant difference in sadness intensity between a viral video and a non-viral video when viewed by female non-football fans. **Where, $t(29) = 2.7333, P = 0.0106$. Hence, we reject the null hypothesis.**

This segment goes to provide an understanding of the differences in arousal between viral video groups (viral video and non-viral video).





H5a: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by male football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by male football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(44) = 0.7981, P = 0.4291$. Hence, we accept the null hypothesis.*

H5b: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by male non-football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by male football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by male football fans. *Where, $t(20) = 0.1952, P = 0.1952$. Hence, we accept the null hypothesis.*

H5c: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by female football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non – viral video by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by female football fans. *Where, $t(12) = 0.4978, P = 0.6276$. Hence, we accept the null hypothesis.*

H5d: There is a significant difference in arousal intensity between a viral video and a non-viral video viewed by Female non- football fans.

An independent samples t-test was performed to compare the arousal intensity between a viral video and a non– viral video by football fans at a 95% CI. The results indicate that there was no significant difference in arousal intensity between a viral video and a non-viral video when viewed by female non- football fans. *Where, $t(29) = 0.1200, P = 0.9053$. Hence, we accept the null hypothesis.*

The results above gave a succinct and descriptive overview of the emotional and arousal intensity variations which is pertinent to the study in understanding diverse viewer behaviour among fan groups. Significantly, the research revealed that emotional variations such as happiness, sadness and anger can occur among gender and fan groups, also not excluding arousal intensity variations. The next section expands and explains on the behavioural concept of “intention to share”.

4.1.1 RESULTS 1b

One of the vital questions on the online web questionnaire was to assess the intention to share a video from the respondents. This is key as the social theory of emotions strongly

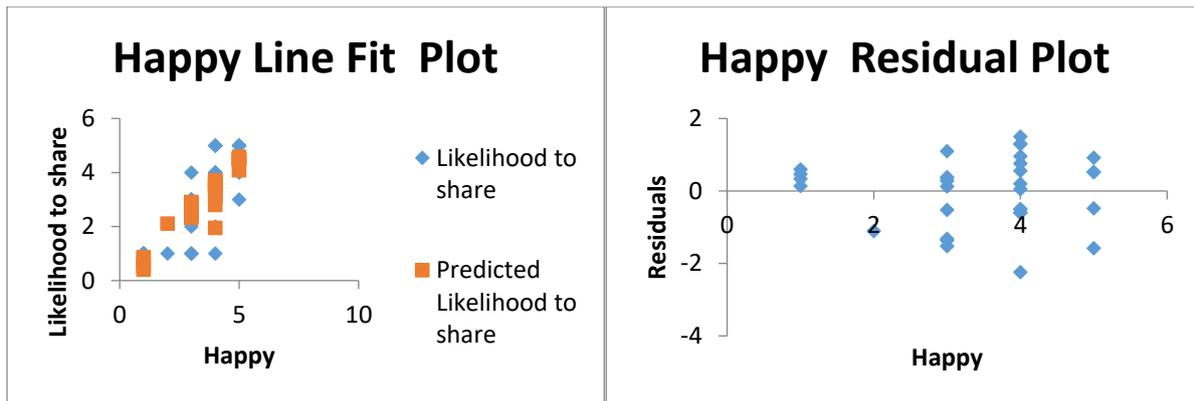
indicates that emotions have a strong part to play in *affecting* the intention to share of a video stimulus which in turn evolves into an **emotional contagion** (e.g. if one's happiness *predicts* a person's likelihood to share) (Rime,2009). The theory also stipulates that after people have experienced an emotional response to content, they consider the option of passing the content on to their social networks. **A multiple linear regression model** was used to analyse the intensity scores for the 6 basic emotions obtained from the questionnaire survey related to the dependent variable which is the, "*intention to share*". Thus, the hypothesis was derived

H1: Emotions are a factor in a football fans intention to share a viral video among football fans.

VIRAL VIDEO 1 (FOOTBALL FANS)

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.76674451							
R Square	0.587897144							
Adjusted R Square	0.488992459							
Standard Error	1.048713257							
Observations	32							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	39.22376259	6.537293765	5.944078	0.00057773			
Residual	25	27.49498741	1.099799496					
Total	31	66.71875						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-0.316966242	0.657854807	-0.481817932	0.634126	-1.671843579	1.037911094	-1.671843579	1.037911094
Happy	0.879685468	0.192054646	4.580391491	0.000111	0.48414152	1.275229416	0.48414152	1.275229416
Sad	0.206686114	0.513996202	0.402116034	0.691016	-0.851908879	1.265281108	-0.851908879	1.265281108
Angry	-0.024780043	0.321660855	-0.077037795	0.939207	-0.687252976	0.63769289	-0.687252976	0.63769289
Surprised	0.099799304	0.15206557	0.656291254	0.517632	-0.2133856	0.412984208	-0.2133856	0.412984208
Scared	-0.984229743	0.660520357	-1.490082374	0.148712	-2.344596884	0.376137398	-2.344596884	0.376137398
Disgusted	0.543290718	0.449376902	1.208986744	0.237978	-0.382218337	1.468799772	-0.382218337	1.468799772

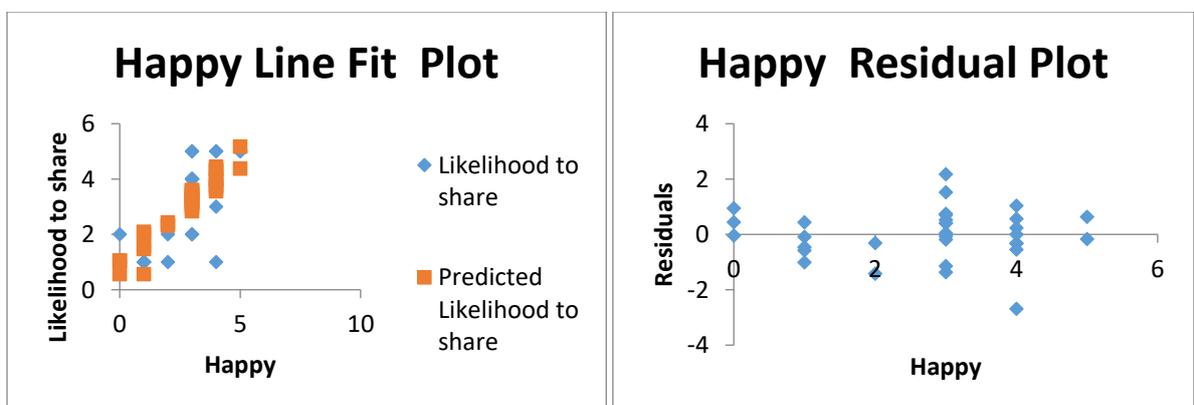
- *The predictor variables data above indicates that only Happiness (i.e $P < 0.0001$) has a significant effect on the intention to share on Football fans.*
- *It is also important to state that 58.78% of the difference in happiness intensity can be explained by the intent to share online.*



VIRAL VIDEO 2 (FOOTBALL FANS)

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.788283796							
R Square	0.621391344							
Adjusted R Square	0.530525266							
Standard Error	1.029613635							
Observations	32							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	43.49739406	7.249565676	6.83854	0.000220711			
Residual	25	26.50260594	1.060104238					
Total	31	70						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.946410881	0.540314903	1.751591297	0.092105	-0.166388492	2.05921025	-0.166388492	2.059210255
Happy	0.73360168	0.171349869	4.281308666	0.00024	0.380700018	1.08650334	0.380700018	1.086503342
Sad	-0.068120894	0.291010949	-0.234083613	0.816826	-0.667469163	0.53122737	-0.667469163	0.531227375
Angry	-0.243512814	0.351317303	-0.693142102	0.49461	-0.967064345	0.48003872	-0.967064345	0.480038716
Surprised	0.111313434	0.152798476	0.728498325	0.473078	-0.203380918	0.42600779	-0.203380918	0.426007785
Scared	-0.097497591	0.173173173	-0.563006321	0.578445	-0.454154418	0.25915924	-0.454154418	0.259159235
Disgusted	0.085411846	0.272977531	0.312889657	0.75696	-0.476795904	0.6476196	-0.476795904	0.647619596

- The predictor variables data above indicates that only Happiness (i.e $P < 0.0002$) has a significant effect on the intention to share on Football fans.
- It is also important to state that 62.14% of the difference in happiness intensity can be explained by the intent to share online.



H2: Emotions are a factor in a football fans intention to share a viral video among non-football fans.

VIRAL VIDEO 1 (NON - FOOTBALL FANS)

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.603415426							
R Square	0.364110176							
Adjusted R Square	0.174135217							
Standard Error	0.9465868							
Observations	28							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	11.28741547	1.881236	2.519438	0.053792777			
Residual	22	19.71258453	0.896027					
Total	28	31						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.746098903	0.311346307	2.396363	0.025495	0.100406182	1.391792	0.100406182	1.391791625
Happy	0.178992905	0.234863932	0.762113	0.454086	-0.308085079	0.666071	-0.308085079	0.666070888
Sad	-1.126391976	0.984671624	-1.14393	0.264949	-3.168475938	0.915692	-3.168475938	0.915691987
Angry	0.052600929	0.988944943	0.053189	0.958061	-1.998345354	2.103547	-1.998345354	2.103547213
Surprised	0.281104786	0.211029642	1.332063	0.196475	-0.156543905	0.718753	-0.156543905	0.718753477
Scared	0	0	65535	#NUM!	0	0	0	0
Disgusted	0.932293833	1.473215648	0.632829	#NUM!	-2.122968423	3.987556	-2.122968423	3.987556089

- The predictor variables data above indicates that no emotion had a significant effect on the intention to share among non-football fans.
- The variability of the model can be explained by 36.41%.

VIRAL VIDEO 2 (NON - FOOTBALL FANS)

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.754312662							
R Square	0.568987592							
Adjusted R Square	0.44584119							
Standard Error	0.730502847							
Observations	28							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	14.7936774	2.465613	4.620416	0.00385235			
Residual	21	11.2063226	0.533634					
Total	27	26						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	1.263166747	0.296574218	4.259193	0.00035	0.646406896	1.879927	0.646406896	1.879926597
Happy	0.102006901	0.204060107	0.499887	0.622353	-0.322359322	0.526373	-0.322359322	0.526373124
Sad	-0.157515553	0.679853166	-0.23169	0.819021	-1.571347609	1.256317	-1.571347609	1.256316503
Angry	-0.551538813	0.353787029	-1.55896	0.13395	-1.287279217	0.184202	-1.287279217	0.184201592
Surprised	0.34341696	0.15423547	2.226576	0.037052	0.022666741	0.664167	0.022666741	0.664167178
Scared	0.218084752	0.531253731	0.41051	0.68559	-0.886717862	1.322887	-0.886717862	1.322887366
Disgusted	0.043463419	0.133545411	0.325458	0.748055	-0.234259466	0.321186	-0.234259466	0.321186304

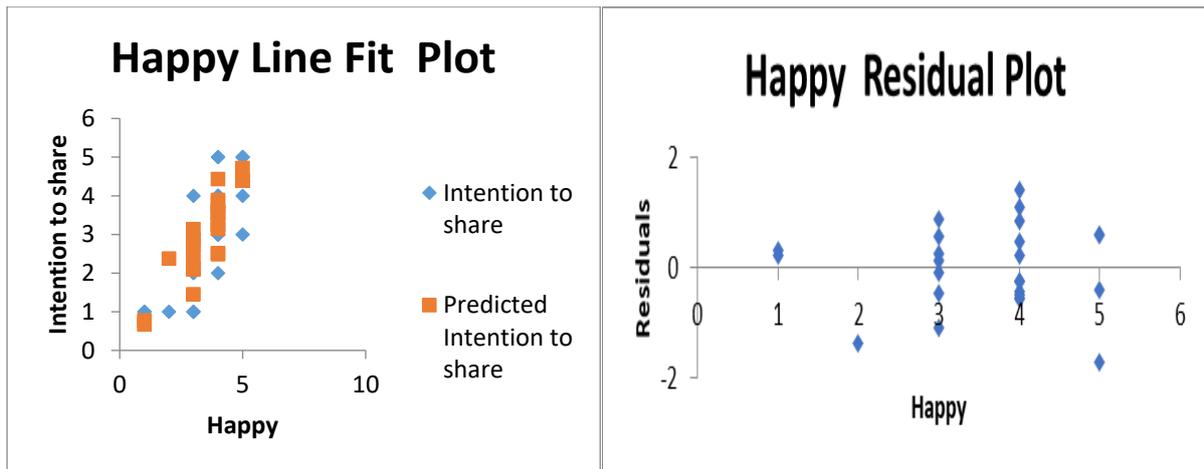
- The predictor variables data above indicates that only Surprise (i.e $P < 0.036$) has a significant effect on the intention to share on Football fans.
- It is also important to state that 56.89% of the difference in surprise intensity can be explained by the intent to share online.

VIRAL VIDEO 1 (MALE FOOTBALL FANS)

H3a: Emotions are a factor in a football fans intention to share a viral video among male football fans.

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.822623867							
R Square	0.676710027							
Adjusted R Square	0.568946703							
Standard Error	0.878399341							
Observations	25							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	29.07146276	4.845244	6.279595	0.001068492			
Residual	18	13.88853724	0.771585					
Total	24	42.96						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-1.019022476	0.730600361	-1.39477	0.180059	-2.553956878	0.515912	-2.553956878	0.515911926
Happy	0.823353702	0.207158648	3.974508	0.000889	0.388129534	1.258578	0.388129534	1.258577871
Sad	0.036902186	0.284662301	0.129635	0.898293	-0.561151117	0.634955	-0.561151117	0.634955488
Angry	0.352133958	0.444656264	0.791924	0.438717	-0.582054188	1.286322	-0.582054188	1.286322103
Sad	-1.444022256	0.787366972	-1.83399	0.083243	-3.098218881	0.210174	-3.098218881	0.21017437
Disgusted	1.59597457	0.981372156	1.626268	0.121272	-0.465811822	3.657761	-0.465811822	3.657760962
Surprised	0.323675193	0.172792665	1.8732	0.077373	-0.039348725	0.686699	-0.039348725	0.686699111

- The predictor variables data above indicates that only Happiness (i.e $P < 0.0009$) has a significant effect on the intention to share on male Football fans.
- It is also important to state that 67.67% of the difference in happiness intensity can be explained by the intent to share online.

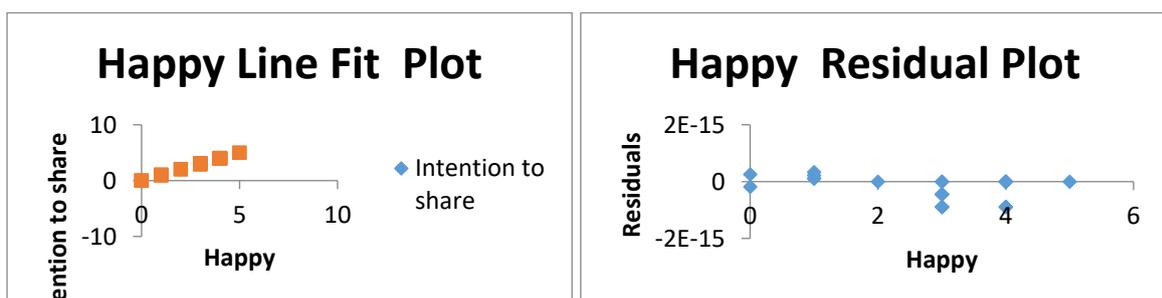


VIRAL VIDEO 2 (MALE FOOTBALL FANS)

H3b: Emotions are a factor in a football fans intention to share a viral video among male football fans.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	1							
R Square	1							
Adjusted R Square	1							
Standard Error	2.54801E-16							
Observations	25							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	6	46	7.666666667	1.18E+32	2.4245E-283			
Residual	18	1.16863E-30	6.49237E-32					
Total	24	46						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-1.38066E-16	1.60073E-16	-0.862519277	0.399748	-4.74368E-16	1.98235E-16	-4.74368E-16	1.98235E-16
Happy	1	5.37555E-17	1.86027E+16	5.2E-283	1	1	1	1
Sad	6.06127E-17	9.09329E-17	0.666565418	0.513504	-1.3043E-16	2.51656E-16	-1.3043E-16	2.51656E-16
Angry	-5.26415E-17	7.32997E-17	-0.718168226	0.481872	-2.06638E-16	1.01355E-16	-2.06638E-16	1.01355E-16
Scared	-7.64963E-17	4.65445E-17	-1.64350941	0.11763	-1.74283E-16	2.129E-17	-1.74283E-16	2.129E-17
Disgusted	3.49911E-17	6.966E-17	0.502312462	0.621537	-1.11359E-16	1.81341E-16	-1.11359E-16	1.81341E-16
Surprised	-1.16383E-16	4.81659E-17	-2.41629528	0.026524	-2.17576E-16	-1.51902E-17	-2.17576E-16	-1.51902E-17

- The predictor variables data above indicates that only Happiness (i.e $P < 5.2E-283$) and Surprise (i.e $P < 0.026$) has a significant effect on the intention to share on male Football fans.
- It is also important to state that 100% of the difference in happiness and surprise intensity can be explained by the intent to share online.



VIRAL VIDEO 1 (FEMALE FOOTBALL FANS)

H4a: Emotions are a factor in a football fans intention to share a viral video among female football fans.

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R		0.986962712						
R Square		0.974095395						
Adjusted R Square		-0.155427632						
Standard Error		0.75						
Observations		7						
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	21.15178571	3.525297619	7.520635	#NUM!			
Residual	1	0.5625	0.5625					
Total	7	21.71428571						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-0.25	1.060660172	-0.23570226	0.852637	-13.7269653	13.2269653	-13.7269653	13.2269653
Happy	1.03125	0.248039185	4.157609203	0.150267	-2.120386672	4.182886672	-2.120386672	4.182886672
Sad	0.21875	1.152019287	0.189883974	0.880538	-14.41904292	14.85654292	-14.41904292	14.85654292
Angry	-5.59375	2.082056901	-2.686646075	0.226843	-32.04879125	20.86129125	-32.04879125	20.86129125
Scared	0	0	65535	#NUM!	0	0	0	0
Disgusted	1.9375	0.609174647	3.180532891	#NUM!	-5.802797779	9.677797779	-5.802797779	9.677797779
Surprised	0.359375	0.347634304	1.033773122	0.489429	-4.057737641	4.776487641	-4.057737641	4.776487641

- The predictor variables data above indicates that no emotion had a significant effect on the intention to share among female football fans.
- The variability of the model can be explained by 97.40%.

VIRAL VIDEO 2 (FEMALE FOOTBALL FANS)

H4b: Emotions are a factor in a football fans intention to share a viral video among female football fans.

<i>Regression Statistics</i>								
Multiple R		1						
R Square		1						
Adjusted R Square		65535						
Standard Error		0						
Observations		7						
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	15.71428571	2.619048	#NUM!	#NUM!			
Residual	0	0	65535					
Total	6	15.71428571						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-4.15303E-16	0	65535	#NUM!	-4.15303E-16	-4.153E-16	-4.153E-16	-4.15303E-16
Happy	1	0	65535	#NUM!	1	1	1	1
Sad	0	0	65535	#NUM!	0	0	0	0
Angry	0	0	65535	#NUM!	0	0	0	0
Scared	0	0	65535	#NUM!	0	0	0	0
Disgusted	0	0	65535	#NUM!	0	0	0	0
Surprised	-1.25939E-17	0	65535	#NUM!	-1.25939E-17	-1.2594E-17	-1.2594E-17	-1.25939E-17

- The predictor variables data above indicates that no emotion had a significant effect on the intention to share among female football fans.

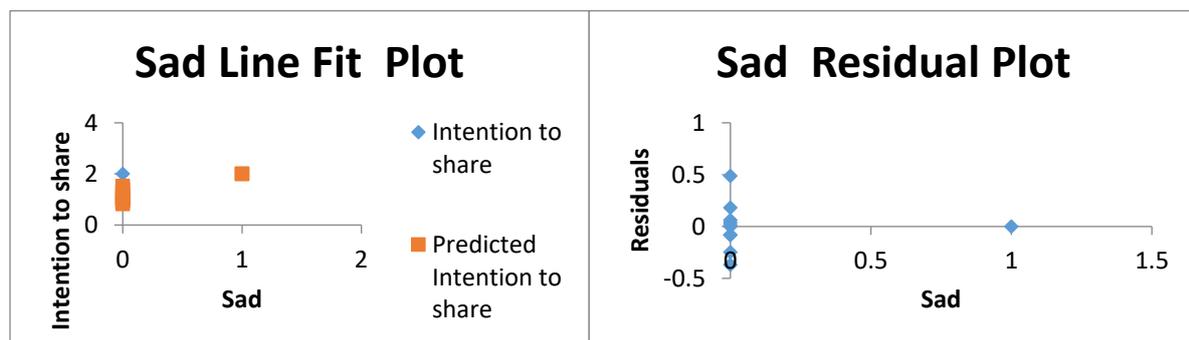
*

VIRAL VIDEO 1 (MALE NON- FOOTBALL FANS)

H5a: Emotions are a factor in a football fans intention to share a viral video among male non- football fans.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.881190349							
R Square	0.776496431							
Adjusted R Square	0.294160718							
Standard Error	0.285085996							
Observations	11							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	6	1.69417403	0.282362338	5.211302211	0.06600638			
Residual	6	0.487644152	0.081274025					
Total	12	2.181818182						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.939044481	0.172796114	5.434407411	0.001610806	0.516227623	1.36186134	0.516227623	1.36186134
Happy	0.263591433	0.153510425	1.717091421	0.136772928	-0.112035044	0.639217911	-0.112035044	0.639217911
Sad	0.894563427	0.307891832	2.905447086	0.027140998	0.141179253	1.6479476	0.141179253	1.6479476
Angry	0	0	65535	#NUM!	0	0	0	0
Scared	0	0	65535	#NUM!	0	0	0	0
Disgusted	0	0.403172482	0	#NUM!	-0.986527525	0.986527525	-0.986527525	0.986527525
Surprised	-0.120263591	0.138855404	-0.866106671	0.419711896	-0.460030524	0.219503341	-0.460030524	0.219503341

- The predictor variables data above indicates that only Sadness (i.e $P < 0.027$) has a significant effect on the intention to share on male Non-Football fans.
- It is also important to state that 77.64% of the difference in sadness intensity can be explained by the intent to share online.

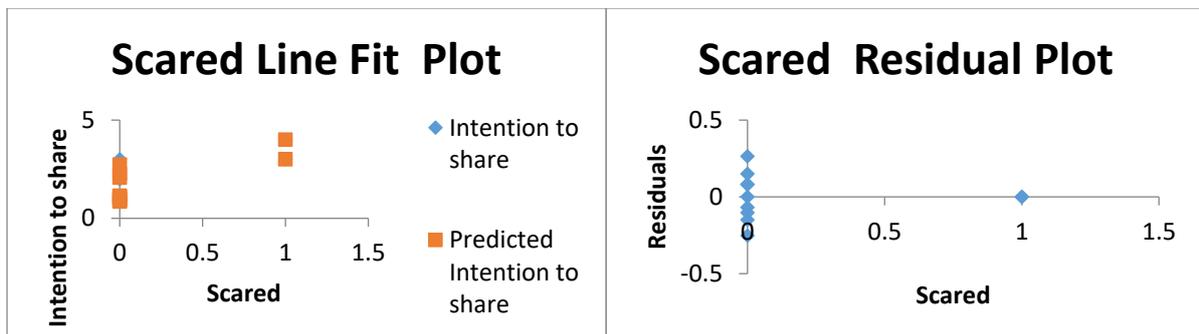


VIRAL VIDEO 2 (MALE NON- FOOTBALL FANS)

H5b: Emotions are a factor in a football fans intention to share a viral video among male non- football fans.

SUMMARY OUTPUT									
Regression Statistics									
Multiple R		0.991070042							
R Square		0.982219828							
Adjusted R Square		0.955549569							
Standard Error		0.227429413							
Observations		11							
ANOVA									
		<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression		6	11.42946708	1.904911181	36.82828283	0.00185214			
Residual		4	0.206896552	0.051724138					
Total		10	11.63636364						
		<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept		0.620689655	0.242607712	2.558408596	0.062743738	-0.052897339	1.294277	-0.052897339	1.294276649
Happy		0.298850575	0.233024539	1.282485422	0.268949209	-0.348129267	0.94583	-0.348129267	0.945830417
Sad		-0.186781609	0.325271617	-0.574232731	0.596558264	-1.089880399	0.716317	-1.089880399	0.716317181
Angry		-0.712643678	0.474894903	-1.500634507	0.207844123	-2.031163306	0.605876	-2.031163306	0.605875949
Scared		1.448275862	0.310344828	4.666666667	0.009541994	0.586620485	2.309931	0.586620485	2.30993124
Disgusted		0.083333333	0.070913579	1.175139303	0.305114848	-0.113554325	0.280221	-0.113554325	0.280220992
Surprised		0.183908046	0.148982545	1.2344268	0.284606331	-0.229733811	0.59755	-0.229733811	0.597549903

- The predictor variables data above indicates that only Fear (i.e $P < 0.001$) has a significant effect on the intention to share on male Non-Football fans. The effect of sharing on fear needs to be further investigated.
- It is also important to state that 98.22% of the difference in sadness intensity can be explained by the intent to share online.

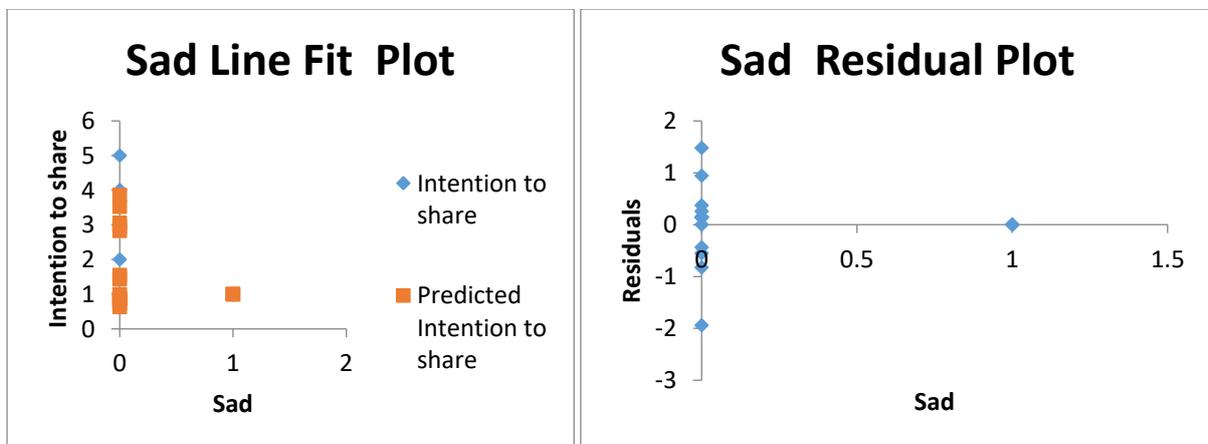


VIRAL VIDEO 1 (FEMALE NON-FOOTBALL FANS)

H6a: Emotions are a factor in a football fans intention to share a viral video among female non- football fans.

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.837407							
R Square	0.70125							
Adjusted R Square	0.435							
Standard Error	0.83316							
Observations	17							
<i>ANOVA</i>								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	19.55249183	3.258749	7.041831	0.003813139			
Residual	12	8.329861111	0.694155					
Total	18	27.88235294						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.857639	0.343660845	2.495597	0.028142	0.108866231	1.606412	0.108866231	1.606411546
Happy	-0.11458	0.255102019	-0.44917	0.661316	-0.670402884	0.441236	-0.670402884	0.441236218
Sad	0	0	65535	#NUM!	0	0	0	0
Angry	-1.94097	0.893194438	-2.17307	#NUM!	-3.887075723	0.005131	-3.887075723	0.005131279
Scared	0	0	65535	#NUM!	0	0	0	0
Disgusted	1.388889	1.0109157	1.373892	#NUM!	-0.813707208	3.591485	-0.813707208	3.591484986
Surprised	0.809028	0.245472032	3.295804	0.00639	0.274190165	1.343865	0.274190165	1.34386539

- The predictor variables data above indicates that only Surprise (i.e $P < 0.027$) has a significant effect on the intention to share on female non-Football fans.
- It is also important to state that 70.13% of the difference in surprise intensity can be explained by the intent to share online.

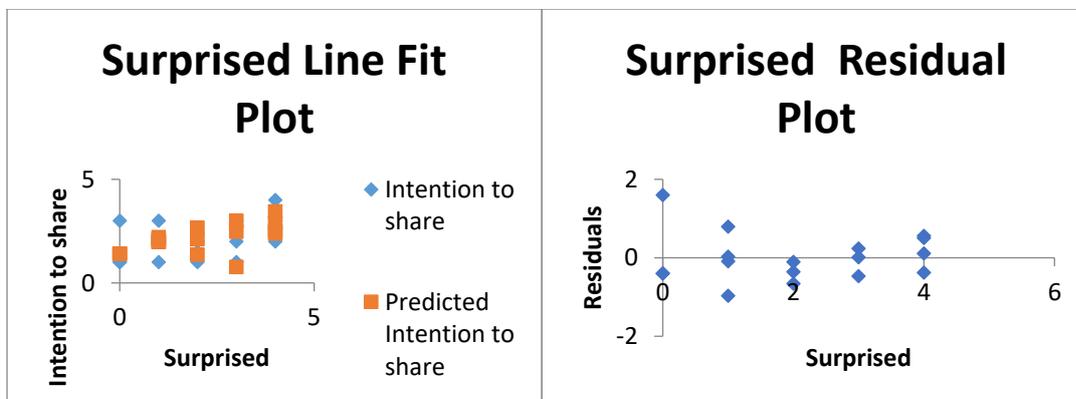


VIRAL VIDEO 2 (FEMALE NON-FOOTBALL FANS)

H6b: Emotions are a factor in a football fans intention to share a viral video among female non- football fans.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.7498457							
R Square	0.5622686							
Adjusted R Square	0.2723906							
Standard Error	0.740101							
Observations	17							
ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	6	7.739461464	1.28991	2.825913	0.070831632			
Residual	11	6.025244419	0.547749					
Total	17	13.76470588						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	1.4010652	0.363238003	3.857155	0.002666	0.601583773	2.200547	0.601583773	2.20054668
Happy	0.1184883	0.230548048	0.513942	0.617459	-0.388944578	0.625921	-0.388944578	0.625921085
Sad	-0.5218882	0.386306911	-1.35097	0.203839	-1.372144001	0.328368	-1.372144001	0.328367553
Angry	0	0	65535	#NUM!	0	0	0	0
Scared	-0.6684664	0.683974465	-0.97733	#NUM!	-2.173884011	0.836951	-2.173884011	0.836951281
Disgusted	0.0089742	0.855424682	0.010491	0.991817	-1.873802858	1.891751	-1.873802858	1.891751202
Surprised	0.4508974	0.18993252	2.373987	0.036891	0.032858759	0.868936	0.032858759	0.868936076

- The predictor variables data above indicates that only Surprise (i.e $P < 0.04$) has a significant effect on the intention to share on female non-Football fans.
- It is also important to state that 56.23% of the difference in surprise intensity can be explained by the intent to share online.



The main findings from the research reveals that behavioural “intention to share” is **directly linked to emotional element of happiness and surprise**. Further analysis is discussed in Chapter 5.1. The next section outlines and explains the role of triggers and its transitional effects on sharing.

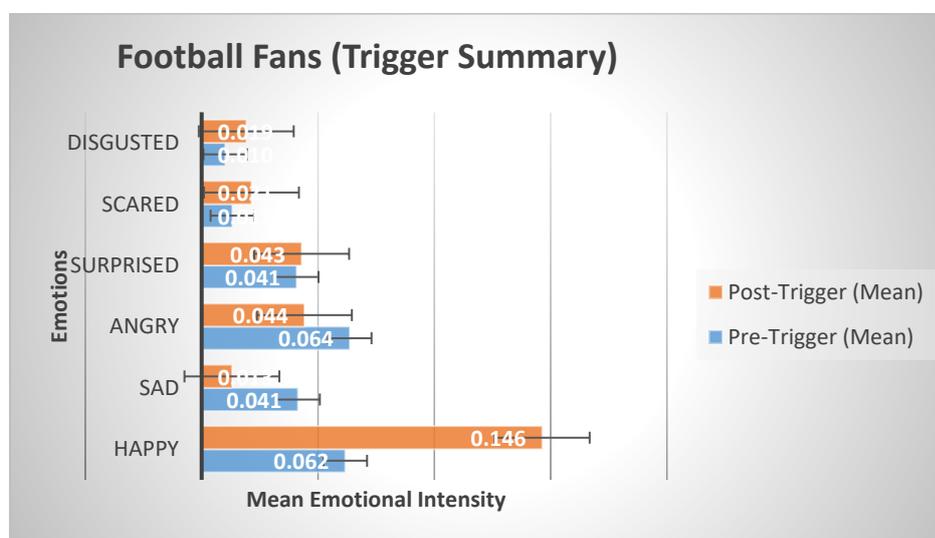
4.1.2 RESULTS 1c

The current research premise construes the fact that people will tend to forward or share a video immediately after viewing the video (Nelson-Field, Reibe and Newstead,2013). The other notion proposed in this thesis is that the intention to share occurs soon after an event or a trigger of events. **For example, a person’s emotional intensity can shift (i.e from low to high or vice versa) after a trigger such as a when a fantastic goal is scored by a footballer (i.e Viral video 1).** To postulate a better understanding of emotional shifts the thesis presupposes that a participant (football fan or non-football fan) who views viral **video 1** will only be inclined to share immediately after the long-range strike occurs (i.e emotional trigger) this trigger will then activate high arousal and elicit sharing intention emotions such as surprise and happiness to create an **emotional contagion. The variations in the emotional trigger can be evident in the diagrams below.**

VIRAL VIDEO 1

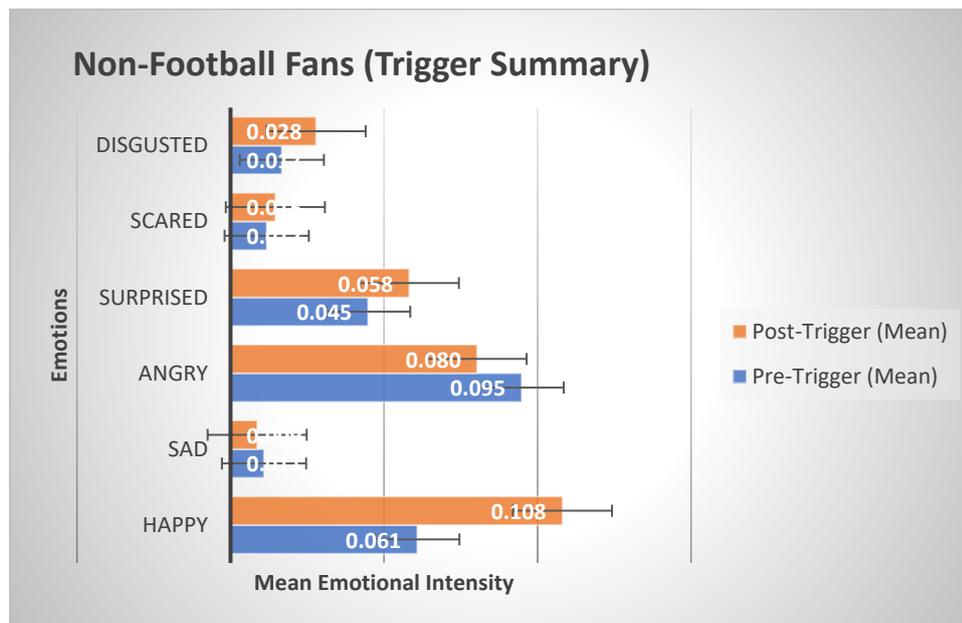
To define a clear distinction the pre-trigger event duration is from 0:00 – 14:00 (Seconds), whilst the post trigger event is from 14:01(Seconds) onwards. (Mean Table 1)

Football Fans						
Emotions	Happy	Sad	Angry	Surprised	Scared	Disgusted
Pre-Trigger (Mean)	0.062	0.041	0.064	0.041	0.013	0.010
Post-Trigger (Mean)	0.146	0.013	0.044	0.043	0.021	0.019
StDev	0.102	0.087	0.142	0.100	0.047	0.022
StDev	0.194	0.026	0.094	0.078	0.078	0.041



(Mean Table 2)

Non-Football Fans						
Emotions	Happy	Sad	Angry	Surprised	Scared	Disgusted
Pre-Trigger (Mean)	0.061	0.011	0.095	0.045	0.012	0.017
Post-Trigger (Mean)	0.108	0.009	0.080	0.058	0.015	0.028
StDev	0.116	0.031	0.227	0.107	0.034	0.060
StDev	0.169	0.021	0.199	0.123	0.044	0.077



It is important within this thesis to evaluate if there is any **significant difference** in the results after a trigger event. Thus, from the observations above the following hypothesis can be defined and evaluated using an independent sample t-test:

H1a: There is a significant difference in happiness intensity among football fans after a trigger.

An independent samples t-test was performed to compare the happiness intensity of football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was a significant difference in happiness intensity before and after a triggered event when viewed by football fans. **Where, $t(62) = 2.1680, P = 0.0340$. Hence, we reject the null hypothesis.**

H1b: There is a significant difference in happiness intensity among non-football fans after a trigger.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in happiness intensity before and after a triggered event when viewed by non-football fans. *Where, $t(54) = 1.2133, P = 0.2303$. Hence, we accept the null hypothesis.*

H2a: There is a significant difference in surprise intensity among football fans after a trigger.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in surprise intensity before and after a triggered event when viewed by football fans. *Where, $t(62) = 0.0834, P = 0.9338$. Hence, we accept the null hypothesis.*

H2b: There is a significant difference in surprise intensity among non-football fans after a trigger.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in surprise intensity before and after a triggered event when viewed by non-football fans. *Where, $t(54) = 0.422, P = 0.6747$. Hence, we accept the null hypothesis.*

H3a: There is a significant difference in anger intensity among football fans after a trigger.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in anger intensity before and after a triggered event when viewed by football fans. *Where, $t(62) = 0.6644, P = 0.5089$. Hence, we accept the null hypothesis.*

H3b: There is a significant difference in anger intensity among non-football fans after a trigger.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in anger intensity before and after a triggered event

when viewed by non-football fans. Where, $t(54) = 0.2629$, $P = 0.7936$. Hence, we accept the null hypothesis.

H4a: There is a significant difference in sadness intensity among football fans after a trigger.

An independent samples t-test was performed to compare the surprise intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in sadness intensity before and after a triggered event when viewed by football fans. Where, $t(62) = 1.7444$, $P = 0.0861$. Hence, we accept the null hypothesis.

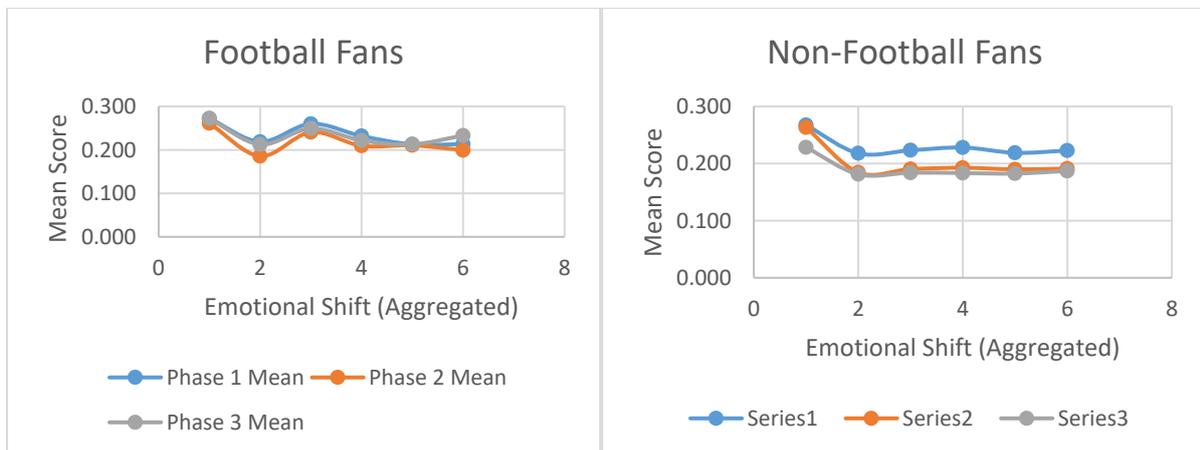
H4b: There is a significant difference in sadness intensity among non-football fans after a trigger.

An independent samples t-test was performed to compare the happiness intensity of non-football fans who watched a viral video 1 at 95% CI (Confidence Interval). The results indicate that there was no significant difference in sadness intensity before and after a triggered event when viewed by non-football fans. Where, $t(54) = 0.2826$, $P = 0.7785$. Hence, we accept the null hypothesis.

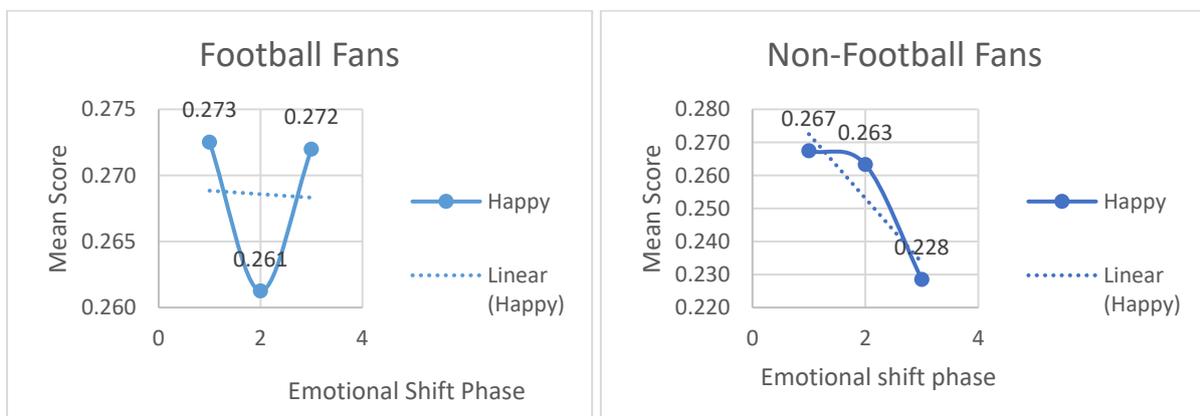
The results revealed the phenomenon of triggers which highlights the period a sharing can occur in a periodic phase. The next section highlights and explains a unique approach using emotional shift patterns to predict viewer behaviour.

4.2 RESULTS 2

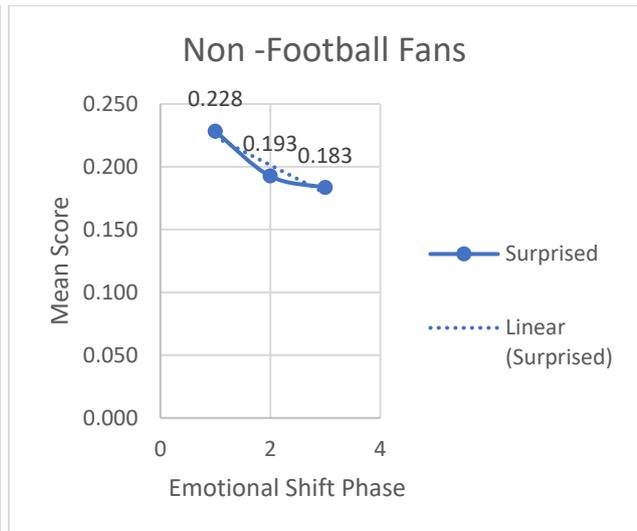
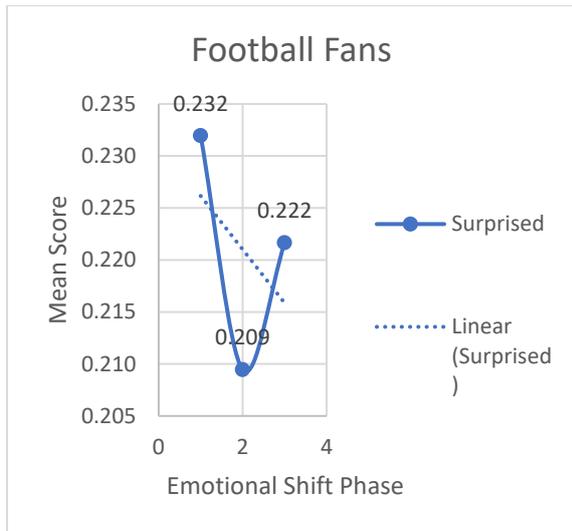
This chapter extends on Analysis 1C where it presupposes that a viral video stimulus can contain multiple trigger events. In such a phenomenon such as in **Viral Video 2** multiple trigger events can be analysed using phases. The phases can be depicted in patterns which can ostensibly be used for predicting a viral content based on its intrinsic characteristics using a bell curve distribution. This research will encapsulate data from viral video 2 to demonstrate how virality be modelled or predicted using emotional patterns. **Viral video 2 has a time duration of 1:31 was divided into three phases: phase 1 (0:00 – 0:30), phase 2 (0:31 – 1:00) and phase 3 (1:01+).** The following is a depiction of the emotional patterns of football fans and non-football fans.



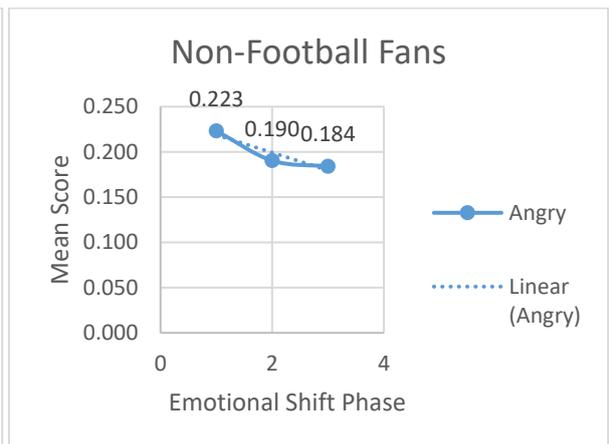
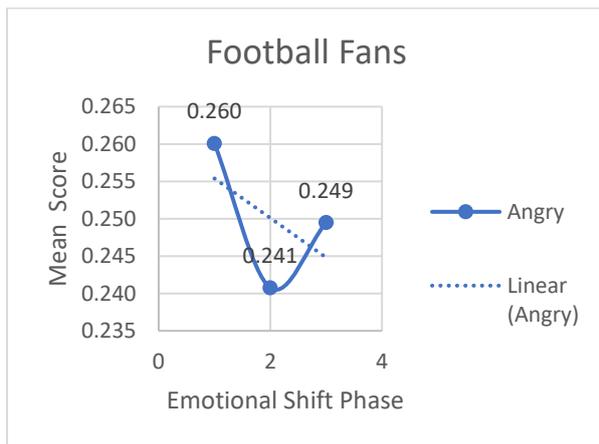
HAPPINESS (VIRAL VIDEO 2)



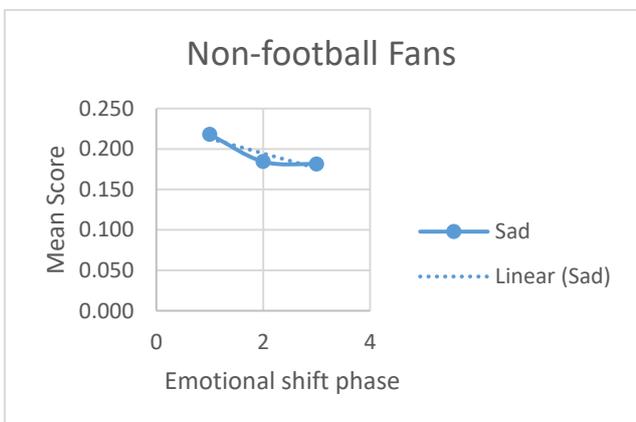
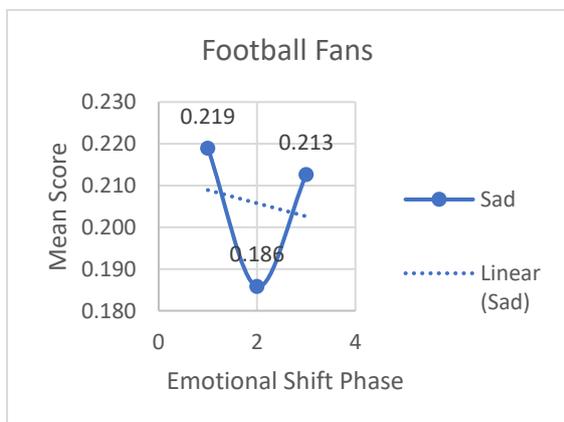
SURPRISE (VIRAL VIDEO 2)



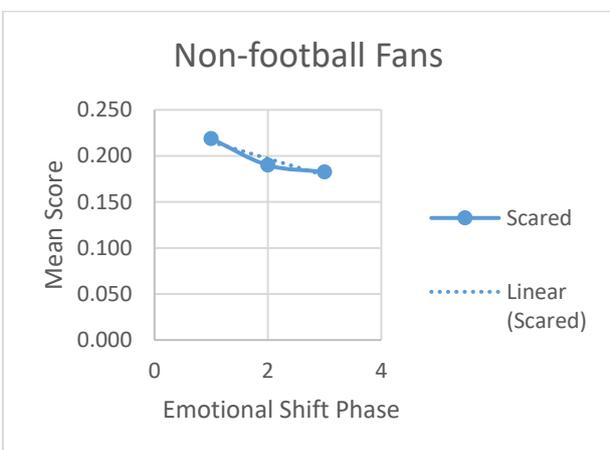
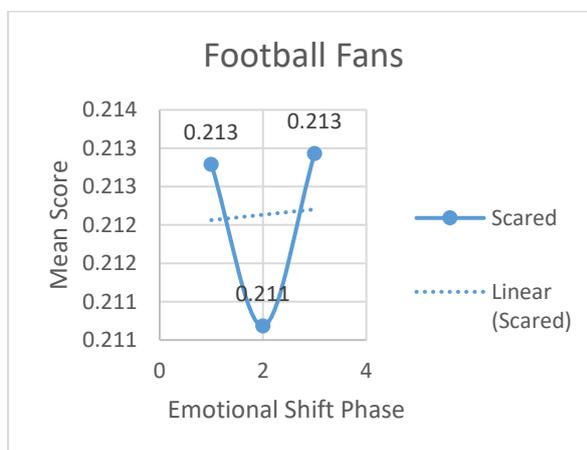
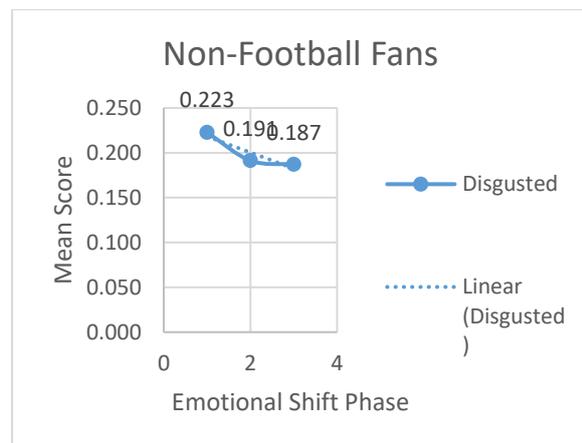
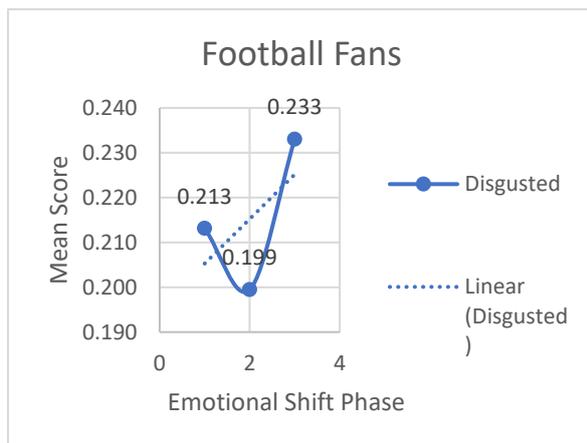
ANGER (VIRAL VIDEO 2)



SADNESS (VIRAL VIDEO 2)



DISGUST (VIRAL VIDEO 2)



The results from the emotional shift phase reveals that distinct patterns can occur for specific fan groups who view a viral video and a non – viral video, with football fans tending to depict an inverted or downwards curve as opposed to non-football fans with happiness exhibiting near perfect downward curve. Further analysis is discussed in chapter 5.2. The next section centres on the methodology with a focus on comparing self-report and facial expression analysis for correctly measuring the emotionality when viewing a viral video stimuli.

4.3 RESULTS 3

In order to adequately analyse the third objective of this thesis it was important to test the validity of the methods to assess if they corroborate with each other (i.e. observation data from facial expression analysis and questionnaire survey). To do so it was integral to evaluate if there exists any relationship between the results data post testing, to cross-validate a Spearman's ranks correlation was used to test the methods in relation to the basic emotions represented.

The results have shown that there exists minimal relationship between the two methods (i.e existence of discriminant validity which tests whether measurements that are not supposed to be related are unrelated). The only significant results were anger, surprise and sadness out of 24 tests where anger indicated $r(31) = -0.398, p = 0.027$, Surprise indicated $r(31) = 0.081, p = 0.035, p < 0.05$ and sadness indicated $r(31) = -0.415, p = 0.020, p > 0.05$.

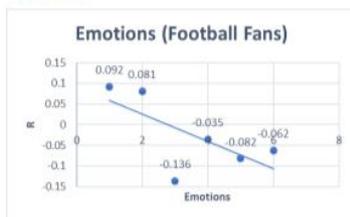
Viral Video 1 (James Poole's Long-range goal)		
	Football Fans	Non -Football fans
Emotions		
Happy	$r(32) = 0.092, P = 0.615, P > 0.05$	$r(28) = 0.235, P = 0.38, P > 0.05$
Surprise	$r(32) = 0.081, p = 0.659, p > 0.05$	$r(28) = -0.237, p = 0.225, p > 0.05$
Anger	$r(32) = -0.136, p = 0.460, p > 0.05$	$r(28) = -0.081, p = 0.682, p > 0.05$
Sadness	$r(32) = -0.035, p = 0.848, p > 0.05$	$r(28) = -0.365, p = 0.056, p > 0.05$
Disgust	$r(32) = -0.081, p = 0.661, p > 0.05$	$r(28) = -0.261, p = 0.180, p > 0.05$
Fear	$r(32) = -0.062, p = 0.736, p > 0.05$	$r(28) = -0.227, p = 0.246, p > 0.05$
Viral Video 2 (Independence Day Ad with Manchester United Stars)		
	Football Fans	Non-Football Fans
Emotions		
Happy	$r(31) = 0.205, P = 0.270, P > 0.05$	$r(27) = 0.215, P = 0.282, P > 0.05$
Surprise	$r(31) = 0.380, p = 0.035, p < 0.05$	$r(27) = 0.202, p = 0.313, p > 0.05$
Anger	$r(31) = 0.398, p = 0.027, p < 0.05$	$r(27) = -0.294, p = 0.137, p > 0.05$
Sadness	$r(31) = -0.415, p = 0.020, p < 0.05$	$r(27) = 0.034, p = 0.865, p > 0.05$

Disgust	$r(31) = -0.233, p = 0.208, p > 0.05$	$r(27) = 0.052, p = 0.799, p > 0.05$
Fear	$r(31) = 0.051, p = 0.787, p > 0.05$	$r(27) = -0.068, p = 0.737, p > 0.05$

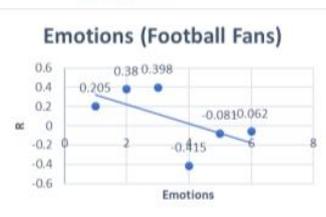
The scatter plot diagrams below indicate further evidence of discriminant validity where an inverse relation is shown between the two methods depicted by a negative downward slope.

R-Coefficient Data (Emotions)

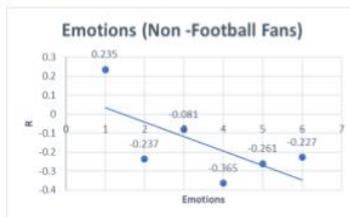
Viral Video 1



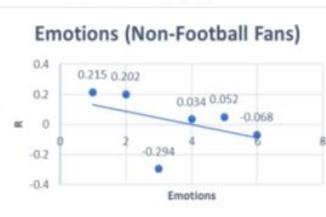
Viral Video 2



Non - Viral Video 1



Non - Viral Video 2



The findings from this research has revealed that there exists **discriminant validity** between the two methods and therefore one method not suitable for the measurement of emotional stimuli (i.e self-report). Further explanation is highlighted in chapter 5.3.

The next section goes on to discuss the empirical findings in relation to literature whilst emphasising the scope of the study.

5.0 DISCUSSION AND FINDINGS

The discussion and findings section of this thesis will provide an insightful and critical overview of the results, where appropriate it will give a brief description of how the research was conducted, a description of the data types, data collection instruments used, and any assumptions made. More importantly, the analysis will be referenced with the literature review for a more comprehensive evaluation of the result findings. Where indicative the researcher's judgment and critical view of the results will be depicted with any emerging themes be acknowledged for the appropriate conclusions in the subsequent chapter.

5.1 DISCUSSION RELATED TO RESULTS 1

There are three essential factors in emotion communication these include touch , language and facial expressions (Zheng et al.,2020). Due to the methodology and scope the thesis adopted, the focus was on the underlying role facial expressions have in aiding the diffusion of emotion of a video stimulus in conjunction with the use of language, which to a lesser extent had a supplementary role. In relation to emotions, particular emphasis were placed on bi-polar emotions such as "happy" and "sad" or "happy" and "anger" within an "in-group" and "out-group" premise and were based on Russel's circumplex model of effect (Posner, Russel and Peterson, 2005). In other words the comparison of emotions within the study took into consideration the opposite arousal or valence.

Though the thesis measured all emotions the main focus was on four (Happiness, Anger, Surprise and Sadness) - instead of all six of Ekman's basic emotions for two reasons: 1) The video stimuli adopted for the study were not targeted to induce "fear" and "disgust" and though some emotional variations of this emotions could show in the data the emotions elicited were negligible 2) happiness, sadness, anger and surprise are the most typical emotions used within emotion recognition research, and the scenarios that use the remaining two are situational and less frequent.

Streamlining further into the results the premier aim of the data presented below was to understand whether viral videos can be characterised by certain emotional responses when elicited from the viewing audience. By differentiating the mean emotional intensity between

the two viral videos and the two non-viral videos the study was able to depict significant findings in the emotional and arousal intensity. See summary below.

Table 8 Validation table 1

Emotions or Arousal	Fan Group	Video Group	Significance
Happiness	Football Fans	Viral video 1 and non-viral video 1	Where, $t(62) = 2.408$, $P = 0.0190$. ¹
Happiness	Football Fans	Viral video 2 and non-viral video 2	Where, $t(61) = 2.0955$, $P = 0.0403$. ¹
Happiness	Female Football Fans	Viral video 1 and non-viral video 1	Where, $t(12) = 2.9658$, $P = 0.0118$.
Anger	Female Football Fans	Viral video 2 and non-viral video 2	Where, $t(12) = 10.4538$, $P = 0.001$.
Sadness	Female Non-Football Fans	Viral video 2 and non-viral video 2	Where, $t(29) = 2.7333$, $P = 0.0106$. ²
High arousal intensity	Non-Football Fans	Viral video 1 and non-viral video 1	Where, $t(53) = 3.8668$, $P = 0.0003$.
High arousal intensity	Non-Football Fans	Viral video 2 and non-viral video 2	Where, $t(51) = 2.2625$, $P = 0.028$. ³
High arousal intensity	Male Football Fans	Viral video 2 and non-viral video 2	Where, $t(61) = 0.7981$, $P = 0.0012$.
High arousal intensity	Male Non-Football Fans	Viral video 1 and non-viral video 1	Where, $t(20) = 2.9315$, $P = 0.0083$.

The findings tend to support existing research where happiness (positive emotion) is the most dominant emotional trait in viral videos (Dobele et al., 2007; Berger and Milkman, 2012; Nelson-Field, Riebe and Newstead, 2013). The extra dimension in relation to fan groups effect

on virality that this research unearthed is that football fans and to a lesser degree female football fans depict a stronger variation in happiness when viewing a viral video as opposed to non-football fans or male non-football fans. Hence, it can be concluded that a characteristic of a viral video is one that evokes a high level of happiness when narrowed down to its intended target. Conversely, it can also be concluded that a characteristic of a non-viral video is one that evokes a high level of sadness when also narrowed down to its intended target.

The findings above support studies that indicate more positive or more negative content is more viral than content that does not evoke emotion, positive content is more viral than negative content (Berger and Milkman, 2012). In relation to the study, the introductory chapter highlighted an example of a man jumping off a rock wall in Sydney only to be confronted by a shark. The study found that "Happiness", "Surprise" and "Admiration" as the top three top emotional responses to viral content (p. 18). The Blendtec blender example that depicted a blender demonstrator blending an iPhone evoked the emotional element of surprise that was a top emotional response to a viral content (p. 21).

This study on the other hand found “happiness”, “high arousal intensity” and to a lesser extent anger as the top three emotional responses to viral content. Hence, partially contradicting Dobele et al., (2007); Berger and Milkman (2012) findings which showed that surprise as being the most significant emotion to characterise virality. **Thus, it can be deduced from the respective findings that a viral video needs either or both of an emotional response of happiness, surprise, anger and high arousal intensity to be characterised as intrinsically viral.** It is also important to note that surprise can be deduced to be a relatively neutral emotion (being pleasant or unpleasant) (Kim and Mattila, 2010). To support this theory, Kim and Mattila (2010) argued that a positive surprise yields a high satisfaction and conversely, a negative surprise indicates a lower satisfaction.

Berger and Milkman (2012) explored the nature of sharing content in a contemporary context as it is an integral part of modern life as people forward newspaper articles to their friends, send restaurant reviews to the neighbours or people pass YouTube videos to their friends. Studies indicate that 59% of people share their content online with others (Allsop, Basett and Hoskins, 2007). Berger and Milkman (2012) noted that though social transmission is both frequent and important, less is known about why certain content are more **viral** than others. The argument is that most marketing departments often create online ad campaigns or

encourage consumer generated content in the hope that people will share the content with others but some of these efforts take off whilst others fail. The theory underlines that emotion shapes online transmission with focus on a content's valence (i.e whether the content is positive or negative) and the specific emotions it evokes (i.e anger, sadness or awe) affect whether it is highly shared (Berger and Milkman, 2012). To contextualise the table below is a summary of emotions and their positive or negative effect on sharing.

Table 9 validation table 2

Emotions responsible for intention to share	Fan Group	Video Group	Significance
Happiness	Football Fans	Viral video 1 ¹	<i>P<0.0001</i>
Happiness	Football Fans	Viral video 2 ¹	<i>P<0.0002</i>
Surprise	Non-Football Fans	Viral Video 2	<i>P<0.036³</i>
Happiness	Male Football Fans	Viral Video 1	<i>P<0.0009</i>
Sadness	Male Non-Football Fans	Viral Video 1	<i>P<0.027</i>
Fear (Scared)	Male Non-Football Fans	Viral Video 2	<i>P<0.00639</i>
Surprise	Female Non-Football Fans	Viral Video 1	<i>P<0.00639</i>
Surprise	Female Non-Football Fans	Viral Video 2	<i>P<0.00328²</i>

A cross validation of data in table (8) and (9) is undertaken and the following deductions are synthesised and analysed.

- **The first major deductions from the synthesised findings to a marketer is that, “produce videos that make your targeted people happy (i.e. football fans) and the people (i.e. football fans) will be happy to share them”.**

In support of the deduction above Rogers, Sharp and Preece (2011) explicated that a person's expressions can trigger emotional responses in others. Thus, when someone smiles it can cause others to feel good and smile back. To contextualise if someone watches a video of two

happy infants playing together, they will become happy, they then will want to share that happy experience with someone else by sharing that video. The YouTube video, “Charlie Bit my finger”, is a perfect example of the phenomenon as it has harnessed over 860 million views since it was posted 11 years ago. The video showed two infants playing together, which evoked intrinsic feelings of happiness.

Figure 23 Charlie bit my finger



- **Produce videos that have a high arousal intensity and if the non-targeted audience find it surprising, they may share it.**

Each emotion is thought to produce coordinated changes in sensory, perceptual, motor, and physiological functions that, when measured, provide evidence of that emotion’s existence (Barrett, 2006). The expression of emotion includes physical actions, such as exclaiming “wow” upon seeing the overhead kick or covering an eyesight when the snake wraps around the young deer. Experiencing emotion, either the physiological changes or the feeling or a combination, often occurs without cognitive appraisal, relying more on the autonomic response which is **high arousal activity** (Evans, 2001; Jenkins, Oatley and Stein, 1998). For example, the subjective experienced feelings when a non-football fan watches a stimulus, such as a Salford City FC footballer scoring a goal from 40 yards on YouTube would perhaps be surprise. **Videos produced that evoke a level of sadness can be found negatively surprising to the non-targeted audience and be an inhibitor to sharing.**

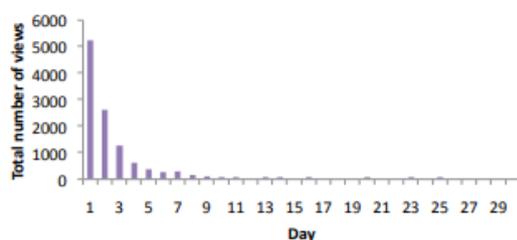
Eckler and Bolls (2011) explains that some emotional engagement is a necessary but not enough for viral success, such that It is unlikely that a video lacking a certain amount of emotion will spread virally, regardless of other factors. Berger and Milkman (2012) noted that sadness is a key deactivator to an intent to share, more so as in this study where the targeted audience is not an interested party. **The other aspect that is important to address is to understand at what point the intention to share occurs or inherently the “trigger”. The part 1c of the results analysis reveals that there is a significant difference in happiness after a trigger $t(62) = 2.1680, p=0.0340$.** This is important to illustrate that events that are marked with high emotional intensity can influence when the sharing trigger occurs.

In summary this chapter was instrumental in establishing that happiness, surprise, anger and high arousal intensity are key emotional variable that characterises virality and happiness in conjunction with surprise being the main factor that necessitates the intention to share to create a **social contagion**. The thesis also highlighted the importance of fan groups in effecting a viral content. The implications of this study to a marketer is that in order to produce a viral content the video stimuli need to have a high level of happiness and high arousal intensity and significantly targeted to the interested audience to instigate a social contagion. The research also showed that to maximise the full effect of instigating a viral content the trigger (i.e marked event) needs to be ascertained in order to understand at what point a video is most “viral”. The subsequent chapter will address an exploratory part of this thesis as it will seek to establish a model to predict a viral content from viewing a stimulus in real time from the data obtained from facial expression analysis.

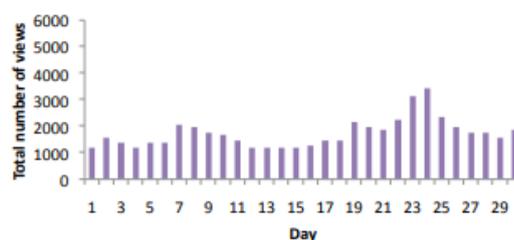
5.2 DISCUSSION RELATED TO RESULTS 2

One of the biggest hurdles marketing managers have is how to predict if a video will have the tendency to go viral. Thus, knowing what factors contribute to virality is essential but harnessing a range of models that explain and predict virality is more advantageous. There have been some models created and tested which purport to predict virality using interactive visualisation systems which rely on the metadata of YouTube videos and statistical algorithms to extrapolate the traction a video will have over time. There have been recent efforts towards building models to predict the virality of online content using various techniques such as reservoir computing, stochastic models of user behaviour and biology inspired survival

techniques (Kong et al.,2013 ; Pinto, Almeida and Goncalves, 2013). However, the gap exists in two folds as there are very few readily available models that allows regular users to easily examine the emotionality of a video stimulus instantaneously to forecast a video’s future virality. The second gap concerns content producers and advertisers who need to choose which videos to promote and to identify potentially viral videos. This thesis solves the gaps by attempting to present a unique predictive model that aggregates the mean emotional intensity of users derived from facial expression analysis and depicts the variations using a normal distribution curve. Pinto , Almeida and Goncalves (2013) noted that the use of historical algorithms can be used for predicting virality with the most common model (Szabo-Huberman) simply predicting the total number of views of a content at a target date based on a linear function on its total number of views at an earlier reference date. Take, for instance, two real YouTube videos whose popularity curves, in terms of the daily number of views for the first 30 days, are shown in Figure below. After 7 days since upload, both videos have very similar total number of views: 10, 665 for video A, and 10, 070 for video B. Thus, the S-H model would predict, using data from these days ($t_r=7$), that both videos would have similar total number of views on the 30th day since upload ($t_t=30$). Yet, they end up with very different total popularities: whereas Figure 1-a) shows a final aggregate popularity that barely exceeds 12, 000 views, the video in Figure 1-b) ends up attracting more than 50, 000 views during the same period. This example illustrates that different YouTube videos (and online content in general) may experience very different **popularity evolution patterns** (Pinto , Almeida and Goncalves, 2013).



(a) Video A: 10,665 at $t_r=7$; 12,060 views at $t_t=30$



(b) Video B: 10,070 views at $t_r=7$; 51,851 views at $t_t=30$

Alternatively, this research is motivated by the observation that if one is monitoring the emotional characteristics of a video that has the tendency to go viral there will be specific viewer patterns as the video is being watched that could give an instantaneous indication if the video is actually a “viral video” as opposed to waiting for a period of time for the video

to gain traction through historical viewing data based on specific reference points as seen in the figure above.

In relation to this thesis the study uncovered that a video which is characterised by a near perfect downward distribution bell curve will indicate “happiness”, as established prior in results 1a and 1b “happiness” is set as a key emotional trait of a viral video and an instigator to share (p.177). This thesis also reveals that patterns within a non-targeted audience will be significantly different (p.179) where non-football fans emotional view patterns tend to drop further down hence, further strengthening our understanding of the role of fan groups as a moderating variable.

5.3 DISCUSSION RELATED TO RESULTS 3

More so, it has been established from prior studies that the facial expression analysis software is an effective method for measuring emotions on its own merit (Terzis, Morides and Economides, 2010; Danner et al.,2014) and supersedes that of a questionnaire survey when used collectively (Zaman and Smith, 2006). With that notion being established in context there are two main implications of undertaking the validity test i.e. where both methods are right and thus show mutual association for the emotions or one method is right, and the other less effective to be used in a research study.

The initial results from this study have shown that there exists minimal relationship between the two methods (i.e existence of discriminant validity which tests whether measurements that are not supposed to be related are unrelated). The results have indicated only three significant results (anger, surprise and sadness) out of 24 tests where $r(31) = -0.398$, $p = 0.027$, $p < 0.05$; $r(31) = 0.081$, $p = 0.035$, $p < 0.05$ and $r(31) = -0.415$, $p = 0.020$, $p > 0.05$. A summary of the validity coefficient indicates that the methods were correlated for only viral video 2 when measuring surprise, anger and sadness in football fans. Sadness indicated a negative correlation which is ambiguous within the scope of the study. In contrast the same video when comparing the emotion of anger in non-football fans also indicates that there is no correlation between the two methods. A further insight into the tests show that the results were significant at a 95% confidence significance level which will support the argument that the likelihood of the significance occurred by chance as opposed to if it had occurred at a

more robust confidence level of 99%. **The significance of the results is that self-report cannot (i.e validating criterion) cannot be used to measure emotionality or be used synchronously with facial expression analysis to reach the same conclusion from their corresponding datasets.** To expand further the findings depict that the questionnaire survey and the facial expression recognition software data is not correlated thereby indicating that one of the methods (i.e Self-report) is less reliable for measuring emotions in videos. This study also argues that the questionnaire survey is a less reliable method using pre-hoc justification from related studies that compared self-report and FaceReader technology though within different contexts (Zaman and Smith ,2006; Harley, 2015).

In summary this chapter argues that contemporary research in virality studies is not only to understand how online virality occurs but in addition how it can be effectively measured. This chapter was responsible for providing a framework to evaluate two main contrasting methods for measuring video virality with the findings from the study indicating the existence of discriminant validity between the two methods which inherently adds to the theoretical advancement with the notion that video marketers or researchers cannot use self-report to measure emotions or use it synchronously with facial expression analysis on online videos. Notwithstanding, even though self-reporting may not be the best indicator for measuring emotionality it can be used to evaluate a user’s intention to share a viral content as seen in Results 1b.

5.4 SUMMARY OF RESEARCH FINDINGS

Based on the thesis the following are main findings obtained from the study.

Table 7

Findings from the study	Explanation
Videos that have a high arousal, happiness, surprise and anger intensity primarily characterise viral videos.	The study indicated that high arousal, surprise and anger are the central elements that characterise viral videos. These findings tend to support previous work undertaken by other researchers such as Berger and

	Milkman (2012) and Riebe, Newstead and Field (2013).
Forwarding behaviour (intention to share) is characterised by the emotional element of surprise and happiness in addition to having an affinity to the subject matter.	The study also indicated that a person's intention to share is characterised by the emotional elements of happiness and surprise which is also consistent with other researchers such as Berger. This, research however extended on this concept and added being part of a group as also an integral variable.
Emotional triggers determine the periodic phase a virality tends to occur.	It emerged from the findings that triggers necessitate at what point virality will occur. The triggers here being important events that are characterised by high arousal and emotional intensity.
Emotional shift patterns can be used to characterise viral video and predict viral video content.	It emerged from the thesis that whilst viewing a video content a person viewing patterns can be created from their emotional response. This is key as this can be used to both characterise viral videos but also be used as a model to predict a viral content in real time. There is an avenue for further studies using both a larger and diverse viewing samples from participants.
There is a correlation between facial expressions and emotions , thus, the FaceReader is a theoretically proven tool for measuring emotions on video content.	The findings helped engage within the central debate as to whether emotions are correlated with facial expressions as it has been the historic notion or the central idea that facial expressions rather depict intentions and social goals. The position of the thesis is that there is ample evidence

	that facial expressions and emotions are intertwined.
Self-Report is not the most robust tool for measuring emotions to determine virality.	The findings revealed the existence of discriminant validity which indicates that the methods used in the evaluation (self-report and FaceReader are un-related).
There is no significant difference between remote users and lab users who undertake a video study where emotions are elicited.	Though beyond the scope of the study, this study showed that there exists no significant difference between Lab users and remote users whose emotions are elicited based on viewing stimuli. There is an avenue for further research within the field usability and cognitive psychology studies.

The next section represents the conclusion which in totality will provide a summary of the research, evaluation of the research goals, critique of the research methodology, research findings and contribution to literature and future research areas.

6.0 CONCLUSION

Fundamentally, the success of the thesis will be in its appraisal of how it contributed to the existing body of knowledge whether by advancing the core study of a particular area, devising a new formula or approach to be used in academia or in practice, using a different methodology or simply developing a unique model. Thus, to empirically evaluate the success of this thesis it is significant to appraise the research questions and hypothesis to understand what this research advanced and what further gaps remain. Thus, in order to validate the contribution to knowledge of this thesis the research questions and hypothesis were refactored in the conclusion as depicted below.

Research Question 1: What is the practical definition of virality within the context of online videos?

From the synthesis of literature and this thesis positioning the simple explanation is that viral videos are videos that gain popularity by being shared and recommended through online and word of mouth processes. While the traditional definition of a viral video only takes account of online sharing and recommendations, the situation as noted from existing literature is more complex. The key question is how we determine the extent of a videos virality? The simplistic answer will be to say views, but the ambiguity will be, “how many views”? Some will argue that it must hit 5 million views in a 3-5-day period others will argue that the actual metric that needs to be considered is the number of shares. **However, Based on the synthesis of literature and devised metric this thesis indicates that a practical definition of a viral video refers to any video stimulus that has a minimum Share Through Rate (STR) of 0.01% within a 3-7 day period which is shared within a specific targeted group and has the tendency to transition to a popular video.** The thesis further determined that a viral video should be categorised into four phases: “weekly trending”, “Gold”, “Platinum” and “Diamond” which is based on a percentile rating (See Appendix A).

Research Question 2: What emotions drive the virality of online video content?

This thesis took a multi approach to studying virality. By combining a broad analysis of virality in the field of literature with a semi-controlled laboratory experiment using the FaceReader and self-report, the thesis documented the characteristics of viral content while also shedding

light on what emotions drive viral transmission of video stimuli among different categories of groups (“in” and “out”). Noteworthy, the thesis findings made significant contributions to the existing literature by evaluating key hypothesis pertinent to this research. Whereas, the research postulated that:

H1: Emotions are a factor in a football fans intention to share a viral video among football fans.

H1: There is a significant difference in happiness (positive emotion) among fan groups who watch a viral video and a non-viral video.

H2: There is a significant difference in surprise (neutral emotion) among fan groups who watch a viral video and a non-viral video.

H3: There is a significant difference in anger (negative emotions) among fan groups who watch a viral video and a non-viral video.

H4: There is a significant difference in sadness (negative emotion) among fans groups who watch a viral video and a non-viral video.

The thesis contributed to inform the ongoing debate about whether negative videos (depicting anger) can have the same level of diffusion traction as positive videos (depicting happiness). **The findings indicate that it depends on the emotional intensity level that a video harnesses.** Every viral video will have **one dominant emotion** and other less dominant emotions that will be evoked. **The most dominant emotion elicited is key into determining whether a video will be diffused or not.** Theoretically, where the most dominant emotion is anger, surprise or happiness that emotion will inherently lead to sharing less so when it’s an emotion depicting sadness. To contextualise, this study highlighted that the most dominant emotions elicited is happiness among both viral videos as evident in the studies original data (See Appendix C). Thus, the finding was instrumental in substantiating existing research where the notion is that happiness (positive emotion) is a key emotional trait in most viral videos.

Significantly, the study also identified that there exists an inverse relationship between happiness & anger and happiness & sadness (See p. 163) – bipolar emotions. Hence, the

higher than happiness is evoked in a video it will correlate with lower sadness and anger. The thesis hypothesises that the same notion could be applied to viral videos where the dominant emotion is anger. The study also noted the relationship between happiness and anger in a non-viral video is less distinct. **Where both Anger is higher in a non-viral video among football fans than happiness, it did not follow the same pattern as anger was found to be higher in viral video 1 but not in viral video 2 (See Appendix C).**

Significantly, the finding above has rejuvenated the importance of the concept of group dynamics (i.e. football fans and non-football fans) which has not been exhaustively explored in other literature. The key point is that though positive emotions and high arousal intensity is important the effect of virality is strengthened when focused on a segment of people who have an affinity or a relationship with the video content being shared. **Based on the data collected football fans showed to have a higher happiness intensity than non-football fans, this ostensibly suggests that forwarding a video content to football fans will have a higher chance of diffusion than non-forwarding to non-football fans due to the level of emotionality evoked amongst both groups (See Appendix C).** Demonstrating these relationships in both the laboratory and in literature, as well as across a large and diverse body of content, underscores the generality of the thesis.

By examining users' **intention to share** the results show some interesting highpoints. Positive video content depicting the emotional elements of surprise and happiness is more likely to be shared thereby creating the catalyst for a social contagion. **This is key as the findings indicate that in order to naturally induce sharing video creators should focus on creating videos with a high happiness, anger, surprise and high arousal intensity.** However, this conclusion needs to be put into context with regards to generalisability of the target audience. Similarly, consistent with the notion that people share to inform others or boost their mood, practically useful and positive content also are elements that enhance diffusion must also be considered and further studies undertaken to understand how they work hand in hand with emotions. More so, the factors are all consistent with the idea that people may share content to help others, generate reciprocity, or boost their reputation.

Substantially, the thesis main aim was to understand which emotions drive video virality. Hence, to have an in-depth understanding of emotions and how it affects viewer behaviour it relied on the emotions explained by Paul Ekman which are happiness, sadness, anger,

surprise, disgust and fear with a much focus on the first four as they are more prominently used within research studies. Fundamental to understanding emotions the literature looked at the criticisms levelled at emotions pertaining to people who have the ability to fake emotions and people actually displaying a different emotion than they intend to. This is significant as this research could potentially measure fake emotions or mocked emotions. In context it can be theorised that it is difficult to spot the difference between “fake” and “real” emotions.

Though the use of the FaceReader technology which was used in this thesis had the advantage to make that distinction it could only do so with other physiological measures which could measure the heart rate. However, the main challenge was not with the technical ability to detect a fake emotional aspect within a video but whether the entire video watched has been “faked” intrinsically, for example, a four minute viral video could have some elements of masked expressions but the majority of the video will have “genuine” emotions elicited by a viewer or viewers. This challenge poses a greater scrutiny and will among other academics be to determine at what level a video needs to be considered faked or partially faked by a viewer or a group of viewers. Due to the ambiguity this thesis admits that some participants emotional data could have been skewed but there is not enough grounds to fully filter out any video until a ubiquitous standard has been developed and appraised by the wider academic community.

Research Question 3: What is the unique way of predicting user emotions from online videos?

The thesis filled another theoretical gap by providing a framework for analysing the viewing patterns of online videos by developing a unique model to predict virality using the emotional data obtained from viewing participants. As indicated prior in the introductory section there are basically two categories of prediction models: The first requires the use of historical statistical data to predict virality and the other uses automatic or real-time models to predict online virality based on User Generated Content (UGC). The unique experimental approach developed for this research takes the latter approach as it does not require any historical data to extrapolate the rate of virality instead it relies on the emotionality elicited from the viewers which can be represented using a mean distribution curve. The advantage of using this approach is that using pattern recognition it will be possible to detect which videos will have

the propensity to go viral in real time and whether the videos are suited to be targeted to a particular audience. **Significantly, the thesis identified that viral videos will have the happiness emotion depict a “perfect downward bell curve”.** However, that perfect downward bell curve was only applicable to football fans as opposed to non-football fans indicating that audience targeting is equally essential. Thus, a marketer will be able to predict based on the models whether a video will not only go viral but if the video will go viral when targeted to a particular group.

It is important to highlight that there are also other current models used for predicting emotions based on video content analysis in real time these are not limited to mid-level concept feature and computational approaches which rely on complex data segmentation and extraction models. Significantly, This thesis used facial expression analysis which distinctively enhanced our understanding of real time modelling of virality using this method. It also advanced our understanding of real time modelling when comparing to other real time and historical predictive approaches that can be used by marketers and researchers for predictive modelling. The framework developed which is based on a distribution bell curve methodology looking at different patterns that tend to characterise both viral and non-viral videos is also unique in its own accord and has not been used in other research studies thereby filling a very important methodological gap.

Research Question 4: What is a more effective method for measuring users emotions when watching a video stimulus when comparing facial expression analysis and self-report?

The primary motive for developing or understanding a new measure designed to tap the same construct of interest as an established measure are basically robustness and convenience. A new measure that is shorter and more robust but leads users to draw the same conclusions as a less robust , more costly measure is a highly desirable alternative. Ideally, before researchers make decisions based on scores from a new measure, they must have evidence that there is a close relationship between the scores of that measure and the performance on the criterion measure. This evidence can be obtained through a **concurrent validation study** which was applied in the thesis. Thus, the strength of the relationship between scores on the new measure and scores on the criterion measure indicates the degree of concurrent validity of the new measure. In the thesis the concurrent validity of the test (i.e. facial expression analysis in this study) was explored with respect to another test (i.e. questionnaire

survey). The thesis had demonstrated in the literature review evidence for the validity of the use of the facial expression analysis thus, the analysis translated to : “How well does facial expression analysis compare with a questionnaire survey?” Where, Test B (i.e questionnaire survey) was used as the **validating criterion**. The thesis tested the concurrent validity of the two measures by estimating the correlating scores on a new measure with scores from the accepted criterion. Based on the test, the thesis was successful in contributing to preliminary evidence where the significance of the results is that self-report cannot (i.e validating criterion) cannot be used synchronously with facial expression analysis to reach the same conclusion from their corresponding datasets. **Thus, if there is an option for a researcher to choose a method to measure emotions of viral videos using the self-report and facial expression analysis , this thesis argues that the use of the FaceReader tool should be used independently to obtain the results.** As using both sets of data will result in significant data discrepancy due to the self-report measure’s inability to measure emotions in real time as opposed to the FaceReader tool.

Furthermore, the thesis also acknowledges that there are other methods to analyse facial expressions apart from facial expression analysis and self-report, these other are primarily focused on signal processing which are not exclusive to FaceReader. Signal processing-oriented analysis fits better with most data intensive set-up studies combining various real-time psychophysiological measures than with this study that focuses on relations of one such variable with a self-report criterion. For example, there are studies that have combined facial expression analysis with ECG, Galvanic Skin Response (GSR) and eye tracking.

The next section outlines the main thesis strengths and weaknesses.

6.1 SUMMARY OF THESIS STRENGTH AND WEAKNESSES

TABLE 8 Strengths and Weakness

STRENGTH	WEAKNESS
<p>Replication</p> <p><i>1. The study can easily be replicated by any researcher as the materials and procedures are clearly spelled out. Statistical outputs</i></p>	<p>Generalisability (Representativeness).</p> <p><i>2. A prime limitation of the study is that majority of the football and non -football</i></p>

<p><i>and analytical conclusions are also clearly depicted for comparative analysis.</i></p>	<p><i>fans gaged for the study were based in the UK (83.33%). Hence, arguably, this study is limited to the UK fan group base.</i></p> <p><i>A similar argument can be said for age groups where up to 60% of the respondents were aged between 21-30.</i></p>
<p>Test of Concurrent Validity</p> <p><i>The study undertook an analysis to assess if the study is measuring the construct it intends to measure by comparing emotions data between two distinct measurements (i.e Facial expression analysis and an online web questionnaire). The findings from the analysis were subsequently translated into a conference paper and presented in a conference for peer academic scrutiny.</i></p>	<p>Intended Scope</p> <p><i>The intended scope of the thesis was to have Salford City FC fans, Football fans (Non-Salford City FC fans) and Non-Football fans for analysis. However, due to the challenges of getting a significant number of Salford City FC fans that option was abandoned, and Salford City FC fans data were respectively aggregated with that of Football fans data. An adequate number of Salford City FC fans will have provided a very robust and granular insight into the effect of in-groups and out-groups influence on virality.</i></p> <ol style="list-style-type: none"> <i>1. Some Salford City FC fans answered the questionnaire but did not undertake the facial expression analysis test. The responses were filtered and invalidated.</i>

	<p>2. <i>The intended scope of the thesis was to utilise two Salford City viral videos. However, at the time of collecting data only one video had gone “viral”. The constraint obligated the research to use a second Manchester United FC commercial video that have gone viral instead. (Barring the constraint, the use of Manchester United FC commercial video provided a comparative insight into the elicitors that affect a memoryless viral video and a viral popular video).</i></p>
<p>Internal consistency</p> <p><i>The statistical analysis of the thesis depicted that there exists some differences between remote users and lab users who partook in the study due to the emotional element of mood.</i></p>	<p>Bias</p> <p>a) <i>A pre-test question was not asked of the participants to ascertain if they might have viewed the video stimuli previously provided for the study. If some of the participants may have seen the footages their emotional responses could be altered and hence differ in response from the first time of viewing the stimuli.</i></p> <p>b) <i>To thoroughly identify micro-expressions the research will have required the use of other physiological measures to measure heart rate remotely such as Photo-plethysmography (PPG) which was</i></p>

	<p><i>not used (Feature or model in newer of advanced versions) and not available in FaceReader 6.1.</i></p> <p><i>c) Race or ethnicity was not captured in the self-report . The omission prevented the research from establishing a validity criterion with respect to ethnicity and thus the FaceReader data with its limitations for evaluating demographics data were used.</i></p>
<p>Stimuli Scope</p> <p><i>Both happy (viral) and neutral (non-viral) stimulus were used to evoke corresponding facial expressions needed for a comparative analysis of the effects of emotionality on virality.</i></p>	<p>Questions pertaining to Mood (Lab and Remote)</p> <p><i>Participants who scored higher on facial expressions of happiness may have been in a generally better mood when entering the experiment and throughout. Control pre-measures were not used in order to prevent priming the participants before the recordings, while post-measures would have been confounded with experimental effects. Instead, the thesis opted to recruit a sufficient sample of reactions and use repeated measures to minimise the influence of mood. As another example, people with different emotion regulation strategies (Gross, 2003) may have exaggerated or in contrast down regulated their facial expressions in the presence of the persuasive stimuli depending on what</i></p>

	<p><i>they deemed appropriate (e.g. because of social desirability).</i></p> <ol style="list-style-type: none"> <i>1. happy facial reactions could be due to presence of people in the selected stimuli – causing participants to simply mimic facial expressions of actors in the advertisements. The thesis did not control for the above-mentioned variables because the objective was in the overall affective reactions (i.e. emotionality) the stimuli provoked and not the characteristics of those videos.</i>
--	---

6.2 KEY CONTRIBUTIONS

This thesis contributes to the literature on digital marketing , cognitive psychology and human in studies. Aside from this thesis, this wider research also enabled other publications. This included a publication in a conference paper and a segment in a popular digital marketing blog post (SemRush). Over the course of this thesis, a significant contribution was made in terms of dissemination. This was made additionally through presentations, teaching and practical contributions, consumed by students, academics and practitioners. This dissemination enabled contributions from this research to digital marketing, social media and video marketing more precisely. In practical terms the thesis contributed to the practical development of a video UX (Video UX) model which is currently being trialled by a video production and marketing company in Manchester who are looking at means to on how to make videos go viral and at the same time justifying a futuristic return on investment. The model is based on the **DUAL-TB model** which was formulated in the thesis (p.23 - 24). Additionally, a basic **Share Through Rate (STR)** formula was devised which can be used by video marketers to evaluate the rate at which videos go viral (p.27).

In academic terms, the completed thesis in itself is a contribution to these, but in terms of impact, the other media described reached more people and created the most discussion. This research was largely inspired by a range of studies including Jonah Bergers' Book - "Contagious why things catch on": who highlighted that more research was needed to uncover our current understanding of why things go viral. This thesis contributed to the literature in this area, rising to these calls. It also widely contributes to the understanding of video marketing for football clubs underpinned by his ideas and other academics.

6.2.1 SOCIAL SHARING OF EMOTIONS (THEORETICAL CONTRIBUTION)

A key contribution from this study was to increase the understanding of the social sharing of emotions theory as applied to video marketing. Though quite a few studies have adopted social sharing of emotions as a theoretical framework this research specifically contributes to the understanding of the ways in which football fans and non-football fans tend to disseminate viral content that is related to football. Studies on what specific emotions drive online videos continuous to be the bone of contention among virality researchers. Happiness , anger, surprise and high arousal were key emotional variables that were found to be a key enabler for video content to go viral whilst sadness was found to be an inhibitor. Additionally, The study findings duly supports other research that found emotions also to be a key factor in the dissemination of viral content (e.g., Bagozzi, Gopinath and Nyer ,1999; Barden, 2018; Berger,2011; Eckler and Bolls, 2011; Nelson-Field, Reibe and Newstead,2011; Guadagno et al.,2013; Jones, Libert and Tynski, 2016; Jones, 2017).

6.2.2 SOCIAL IDENTITY THEORY (THEORETICAL CONTRIBUTION)

Another key contribution from this study was to increase the understanding of the social identity theory as applied to video marketing. A few studies have theorised that a person's demographic such as age or gender on virality can have an effect on virality (Dobele et al., 2007;Hargittai and Walejko, 2008), However more research needed to be undertaken as this thesis strongly supports the notion that belonging to a specific social group (i.e fan group, gender and age) can play key roles to the extent a video content is shared. The research further brought insight into understanding network dynamics , social contagion and planned behaviour. For example, the research findings revealed that Female football fans will be more

emotionally evoked to share a video content that makes them happy as opposed to male football fans. In the wider context this will mean that marketers who intend to create and drive a football related viral video should target female football fans as a starting point.

6.2.3 METHODOLOGICAL CONTRIBUTION

The combination of the two quantitative methods used as part of the study contributes to the literature on virality. The two methods adopted were facial expression analysis and self-report – the mixed methods presents a methodological contribution on its own merit. From the two methods, the data gathered from facial expression analysis was the most targeted in order to answer the research questions. Because of the nature of the positivist study the data gathered was very valuable in deriving rich insights specifically in relation to establishing the validity of the emotional and demographic data via cross validation. The findings from this thesis revealed that the self-report cannot (i.e validating criterion) cannot be used to measure emotionality or be used synchronously with facial expression analysis to reach the same conclusion from their corresponding datasets. Furthermore, the thesis provided a general framework to evaluate two main contrasting methods for measuring video virality with the findings from the study indicating the existence of discriminant validity between the two methods. Though, the two methods showed discriminant validity in relation to the measurement of emotions, the demographic data can be cross validated and this thesis supports the framework for using self-reports data as the validating criterion for demographic data as opposed to the FaceReader due to the algorithmic challenges of robustly identifying a person's data. The mixed methods utilised is also an important data source for brands to understand more about their audiences. Data is a fundamental aspect of the buyer persona spring used to create a video marketing strategy.

6.3 FUTURE RESEARCH

There are numerous avenues for future research within the scope of this study. Particularly when looking at the role that emotion and groups dynamics play in the spread of viral video content online. However, the most obvious future research direction resulting from this study is an understanding into the role of emotions in purchasing. As much as video marketers will want to increase their brand presence and customer engagement through going viral the

finite aim is to lure the viewer of an ad to make a purchase of a product or utilise a service that it is advertising. Thus, the next advancement in this research will be to explore which emotions are a catalyst that leads to a conversion using a similar conceptual framework and methodology undertaken in this study. There already has been some initial contemporary work in this field of understanding emotions and purchase intentions on a theoretical level (Adcock, 2016; Baggozi et al.,2016).However, further research is also needed to discover more relations between patterns of facial expressions and people’s reactions to persuasive stimuli where it will be possible to setup a virtual mock supermarket where people see the presentation of the product (or actual advertisement) and can “buy” it.

Expanding further the research can also take into consideration the predictive model developed to determine video predictability which is in its nascent exploratory phase. There is the avenue to make it more generalisable by expanding the sample size of the patterns in more advanced studies. A more comprehensive outlook should either provide further evidence that emotional viewing patterns harness predictive characteristics or provide yet unexplored facets that will require further investigation. There is the potential for an interdisciplinary approach with data science and computer algorithms studies to help determine content using artificial intelligent systems to ascertain the propensity of videos to go viral in real time. In terms of the methodology subsequent studies should also take an in-depth look at Emotional Retrospective Think Aloud (ERTA) method in conjunction with facial expression analysis. The ERTA emotion measures feeling where users are asked to elicit the emotions in words when a video is replayed after an eye tracking session (Petrie and Precious,2010). The additional qualitative approach will provide insight that cannot be captured by just facial expression analysis such as the nuances of “why”?

6.4 REFLECTIONS ON MY ROLE AS A RESEARCHER

This concluding section switches to the first person in order to outline the final reflections of the researcher in order to aid the concluding part of the study and connect with the researcher motivations in the introduction. Looking in retrospect at my thesis proposal and the final written thesis any reader will notice an inherent evolution not just in terms of substance of where the research was leaning but also as a researcher. My journey as a PhD student needed me to appraise the research in numerous folds. Due to my research being an

inter-disciplinary one which combines elements of video marketing, cognitive psychology and some aspects of sociology and statistics I had to soak in as much knowledge from different fields as possible. Having worked in digital marketing in the industry prior to commencing my research and undertaking a partial business first degree my understanding of marketing principles will be considered sound. However, areas such as cognitive Psychology and some aspects of sociological theories needed to be elevated to the standard that will have enabled me to successfully complete the thesis. As per the requisites I audited a post graduate class in my first year in media Psychology to have a more profound understanding of Psychology principles and applications. Significantly, I also had to learn how to undertake lab experiments with participants and with different psychological measures such as using the Eye Tracking tool, Galvanic Skin Response, Retrospective Think Aloud protocols and using the Automatic Face Reader technology which was fundamentally harnessed in this thesis.

An exhaustive reading of literature helped me gain a more nuanced understanding of virality more specifically as it pertains to this thesis. In relation to literature read and evaluated, the scholarly works of Jonah Berger and Paul Ekman were a very huge influence on my thesis which is resonated in the number of major references attributed to them. I have further had the opportunity to present my research in two UKAIS (United Kingdom Academy for Information Systems) conferences and had my work published in one where I received constructive criticism which helped to validate the ideas of my thesis. In terms of scope I have also had a chance to see how viral videos become viral in relation to Football clubs as Salford City Football Club (SCFC) was the club in focus. The wider accepted school is that emotions drive virality but I have always felt that there was another missing variable that will serve as a catalyst and that is the social identity of a person of where the person has a sense of belonging to (i.e. "In group" and "out group"). For instance, the research was able to successfully theorise that football fans, more specifically female football fans are better sharers of football content and do help facilitate the social contagion of videos and thus, can be targeted as part of a wider marketing campaign strategy. The thesis fundamentally evolved my understanding of video virality from the nuanced concept that it is all about views with more profound notion that it also incorporates the rate of dissemination and popularity of a video which is an important facet in measuring virality. My advice to any researcher yearning to replicate and further this thesis is to address primarily the limitations outlined.

REFERENCES

A

Adage.com. (2015). *Walmart Crushes Holiday Video Views, but One Bona Fide Spiritual Message Gets Through Too*. [online] Available at: <http://adage.com/article/advertising/holiday-viral-campaigns-2015/301853/> [Accessed 28 Jul. 2016].

Adcock, P. (2016). *How emotions influence purchasing behaviour*. [online] LinkedIn.com. Available at: <https://www.linkedin.com/pulse/how-emotions-influence-purchasing-behaviour-phillip-adcock/> [Accessed 9 Jul. 2018].

Agrawal, A. (2016). *Forbes Welcome*. [online] Forbes.com. Available at: <http://www.forbes.com/sites/ajagrawal/2016/01/03/3-reasons-why-you-should-be-marketing-on-youtube-and-periscope/#5d752ee868d0> [Accessed 12 Oct. 2016].

Allsop, D., Bassett, B. and Hoskins, J., 2007. Word-of-Mouth Research: Principles and Applications. *Journal of Advertising Research*, 47(4), pp.398-411.

Asamoah, J. (2016) "How to measure and predict video virality": A statistical approach. UKAIS Conference in Information Systems, February 2016. (Abstract and full paper accepted).

Astolfi, L., Vecchiato, G., De Vico Fallani, F., Salinari, S., Cincotti, F., Aloise, F., Mattia, D., Marciani, M., Bianchi, L., Soranzo, R. and Babiloni, F. (2009). The Track of Brain Activity during the Observation of TV Commercials with the High-Resolution EEG Technology. *Computational Intelligence and Neuroscience*, 2009, pp.1-7.

Atkinson, C. (2012). *What Makes a Video Go Viral? 3 Unruly Tips for Viral Video Success*. [online] Tubular's Insights. Available at: <http://www.reelseo.com/what-video-viral-3-unruly-tips-success/> [Accessed 28 Jul. 2016].

B

- Bamberg, S. (2002). Effects of implementing intentions on the actual performance of new environmentally friendly behaviours — results of two field experiments . *Journal of Environmental Psychology*, 22(4), pp.399-411.
- Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., and Wallace, M. (2008). The Effects of the Social Structure of Digital Networks on Viral Marketing Performance. *Information Systems Research*, 19(3), 273–290. doi:10.1287/isre.1070.0152.
- Bagozzi, R., Gopinath, M. and Nyer, P. (1999). The Role of Emotions in Marketing. *Journal of the Academy of Marketing Science*, 27(2), pp.184-206.
- Bagozzi, R., Belanche, D., Casaló, L. and Flavián, C. (2016). The Role of Anticipated Emotions in Purchase Intentions. *Psychology & Marketing*, 33(8), pp.629-645.
- Barasch, A. and Berger, J. (2014). Broadcasting and Narrowcasting: How Audience Size Affects What People Share. *Journal of Marketing Research*, 51(3), pp.286-299.
- Barden, P., 2018. *How Emotion Really Works In Advertising | WARC*. [online] Warc.com. Available at: <<https://www.warc.com/content/paywall/article/admap/how-emotion-really-works-in-advertising/122100>> [Accessed 12 March 2020].
- Barr, A. (2015). *Google Mistakenly Tags Black People as ‘Gorillas,’ Showing Limits of Algorithms*. [online] WSJ. Available at: <https://blogs.wsj.com/digits/2015/07/01/google-mistakenly-tags-black-people-as-gorillas-showing-limits-of-algorithms/> [Accessed 5 Mar. 2020].
- Barrett, L. (2006). Valence is a basic building block of emotional life. *Journal of Research in Personality*, 40(1), pp.35-55.
- Barrett, L. (2006). Are Emotions Natural Kinds?. *Perspect on Psych Science*, 1(1), pp.28-58.
- Bartlett, M., Littlewort - Fort, G., Movellan, J., Fasel, I. and Frank, M., 2014. *Automated Coding Facial System*. 8798374 B2.
- Bartlett MS, Hager JC, Ekman P, Sejnowski TJ. Measuring facial expressions by computer image analysis. *Psychophysiology*. 1999;36(2):253–63.

Benta, K., Kuilenburg, H., Xolocotzin Eligio, U. and den Uy, M. (2009). Evaluation of a System for Real-Time Valence Assessment of Spontaneous Facial Expressions. Cluj-Napoca: International Romanian – French Workshop.

Berger, J. (2011). Arousal Increases Social Transmission of Information. *Psychological Science*, 22(7), pp.891-893.

Berger, J. and Milkman, K. (2012). What Makes Online Content Viral?. *Journal of Marketing Research*, 49(2), pp.192-205.

Berger, J. and Schwartz, E. (2011). What Drives Immediate and Ongoing Word of Mouth?. *Journal of Marketing Research*, 48(5), pp.869-880.

Berger, J. (2013). *Contagious why things catch on*. New York: Simon and Schuster, pp.21-27.

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, 24(4), pp.586-607.

Bhattacharjee, A. (2012) *Social Science Research: Principles, Methods, and Practices*. Open University Press, USF Tampa Bay.

Botha, E. (2014). A means to an end: Using political satire to go viral. *Public Relations Review*, 40(2), pp.363-374.

Brace, I. (2004). Questionnaire design: How to plan, structure and write survey material for effective market research. Kogan Page: London

Bryman, A., 2012. *Social Research Methods*. 4th ed. Oxford: Oxford University Press.

Bryman, A. and Bell, E., 2011. *Business Research Methods*. Cambridge: Oxford University Press.

Broxton, T., Interian, Y., Vaver, J., and Wattenhofer, M. (2010, 13-13 Dec. 2010). Catching a Viral Video. Paper presented at the Data Mining Workshops (ICDMW), 2010 IEEE International Conference.

Burns, A. and Bush, R., 2010. *Marketing Research*. 6th ed. Pearson.

C

Camarero, C., & San José, R. (2011). Social and attitudinal determinants of viral marketing dynamics. *Computers in Human Behaviour*.

Cameron-Bandler, L. and Lebeau, M. (1986). *The emotional hostage: Rescuing your emotional life*. Real People Press: Moab, UT.

Carr, A., 2019. *Controlling Emotions: Is It Possible?*. [online] Ashleycarrcounseling.com. Available at: <<https://www.ashleycarrcounseling.com/post/controlling-emotions-is-it-possible>> [Accessed 11 June 2020].

Carroll, J. and Russell, J., 1996. Do facial expressions signal specific emotions? Judging emotion from the face in context. *Journal of Personality and Social Psychology*, 70(2), pp.205-218.

Crivelli, C. and Fridlund, A. (2018). Facial Displays Are Tools for Social Influence. *Trends in Cognitive Sciences*, 22(5), pp.388-399.

Cha, Meeyoung, Haewoon Kwak, Pablo Rodriguez, Yong-Yeol Ahn, and Sue Moon. I tube, you tube, everybody tubes: analyzing the world's largest user generated content video system. In *Proceedings of IMC'07*, pages 1–14, New York, NY, USA, 2007. ACM

Cheal, J. (2012). Science, Philosophy and NLP. *Neuro Linguistic Programming*, Vol. 29.

Chen, Z. and Berger, J., 2013. When, Why, and How Controversy Causes Conversation. *Journal of Consumer Research*, 40(3), pp.580-593.

Chohan, R., 2013. *Understanding The Role Of Emotions In Viral Marketing*. Masters. University of Cape Town.

Crivelli, C. and Fridlund, A. (2018). Facial Displays Are Tools for Social Influence. *Trends in Cognitive Sciences*, 22(5), pp.388-399...

Chiu, C., Hsu, M. and Wang, E. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision Support Systems*, 42(3), pp.1872-1888.

Christophe V. and Rimé B. (1997). Exposure to the social sharing of emotion: emotional impact, listener responses and the secondary social sharing, *European journal of social psychology*, 27, 37–54.

Chen, Z. and Berger, J. (2013). When, Why, and How Controversy Causes Conversation. *Journal of Consumer Research*, 40(3), pp.580-593.

Choliz, M.; Fernandez-Abascal, E.G. (2012). Recognition of emotional facial expressions: the role of facial and contextual information in the accuracy of recognition, *Psychological reports*, 110 (1), 338-350.

Chu, S. C. (2011). Viral advertising in social media: participation in Facebook Groups and Responses among college-Aged users. *Journal of Interactive Advertising*, 12(1), 30.

Chu, S. and Kim, Y., 2011. Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. *International Journal of Advertising*, 30(1), pp.47-75.

CIRT (2018). *Types of Experimental Research Designs - Center for Innovation in Research and Teaching*. [online] Available at:

https://cirt.gcu.edu/research/developmentresources/research_ready/experimental/design_types [Accessed 31 May 2018].

Cisco (2015). *Cisco Visual Networking Index: Forecast and Methodology, 2014–2019*. [online] Available at: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/ip-ngn-ip-next-generation-network/white_paper_c11-481360.pdf [Accessed 12 Oct. 2015].

Clampa and Goeldi (2013). White paper title [Pixability : The top 100 global brands – Key lessons for success on YouTube].

Cohen, R. J., and Swerdlik, M. E. (2009). *Psychological testing and assessment: An introduction to tests and measurement (7th ed.)*. New York, NY: McGraw-Hill.

Cohn, J.F., Ambadar, Z., and Ekman, P. (2007). Observer-based measurement of facial expression with the Facial Action Coding System.

Cohn JF, Ekman P. Measuring facial action. In: Harrigan J, Rosenthal R, Scherer K, editors. *The New Handbook of Methods in Nonverbal Behavior Research*. New York, NY: Oxford University Press; 2005. p. 9–64 ff

Coghlan, D., and Brannick, T. (2014). *Doing action research in your own organization*. Sage.

Crane, R., & Sornette, D. (2008). Robust dynamic classes revealed by measuring the response function of a social system. *Proceedings of the National Academy of Sciences*, 105, 15649 - 15653.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publication.

Creswell, J. W., & Clark, V. L. P. (2007). *Designing and conducting mixed methods research*.

Cruz, D., and Fill, C. (2008). Evaluating viral marketing: isolating the key criteria. *Marketing Intelligence and Planning*, 26(7), 743–758. doi:10.1108/02634500810916690.

D

Danner, L., Sidorkina, L., Joechl, M. and Duerschmid, K. (2014). Make a face! Implicit and explicit measurement of facial expressions elicited by orange juices using face reading technology. *Food Quality and Preference*, 32, pp.167-172.

D'arcey, T. (2013). *ASSESSING THE VALIDITY OF FACEREADER USING FACIAL EMG*. Masters Thesis. California State University.

De Ruyter, K. and Bloemer, J. 1999. Customer loyalty in extended service settings: the interaction between satisfaction, value attainment and positive mood. *International Journal of Service Industry Management*, 10(3): 320–36.

Denscombe, M. (2003). *The Good Research Guide: For Small-Scale Social Research Projects*, 2nd ed. London: Open University Press

Dobele, A., Lindgreen, A., Beverland, M., Vanhamme, J. and van Wijk, R. (2007). Why pass on viral messages? Because they connect emotionally. *Business Horizons*, 50(4), pp.291-304.

Dray, Susan & Siegel, David. (2004). Remote possibilities? International usability testing at a distance. *Interactions*. 11. 10-17.

Duran, N. D.; Dale, R.; Kello, C. T.; Street, C. N.; and Richardson, D. C. 2013. Exploring the movement dynamics of deception. *Frontiers in psychology* 4.

E

Easterby-Smith, M., Thorpe, R. Jackson, P. & Lowe, A. (2008) *Management Research*. 3rd edn. Sage: London.

Eckler, P. and Bolls, P. (2011). Spreading the Virus. *Journal of Interactive Advertising*, 11(2), pp.1-11.

Edwards, P., Roberts, I., Clarke, M., DiGiuseppi, C., Pratap, S., Wentz, R., & Kwan, I. (2002). Increasing response rates to postal questionnaires: systematic review. *BMJ (Clinical research ed.)*, 324(7347), 1183.

Ekman, P. (1972). Universals and Cultural Differences in Facial Expressions of Emotions. In Cole, J. (Ed.), *Nebraska Symposium on Motivation* (pp. 207-282). Lincoln, NB: University of Nebraska Press.

Ekman, P., and Friesen, W. V. (1978). *The Facial Action Coding System*. Palo Alto, CA: Consulting Psychological Press.

Ekman, P., Friesen, W. V., & Ellsworth, P. (1982). Research foundations. In P. Ekman (Ed.), *Emotion in the human face* (2nd ed., pp. 1-143). New York: Cambridge University Press.

Ekman, P. (1982). Methods for measuring facial action. In K. R. Scherer and P. Ekman (Eds.), *Handbook of methods in nonverbal behavior research*. Cambridge: Cambridge University Press.

Ekman, P. and Davidson, R.J. (eds.) (1994). *The nature of emotion: Fundamental questions*. Series in Affective Science. Oxford University Press: New York, NY.

Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion*, 6(3-4), pp.169-200.

Ekman, P. (1993). Facial expression and emotion. *American Psychologist*, 48(4), pp 92-384.

Ekman, P. (1994). All emotions are basic. In Paul Ekman and Richard J Davidson (eds.).

The nature of emotion: Fundamental questions. Oxford University Press: New York, NY.

Ekman, P. (ed.) (2003). *Emotions inside out: 130 years after Darwin's the Expression of the Emotions in Man and Animals*. New York Academy of Sciences: New York: NY

Ekman, P. and Friesen, W., 2003. *Unmasking The Face*. Cambridge (Mas.): Malor Books.

Ellis, J., Lin, S., Ling, C. and Fu-Chang, S. (2014). Predicting Evoked Emotions in Video. In: *International Symposium on Multimedia*. New York: IEEE.

Evans, D. (2001). *Emotion: a very short introduction*. Oxford University Press: Oxford

Eysenbach, G. and Köhler, C. (2002). How do consumers search for and appraise health information on the world wide web? Qualitative study using focus groups, usability tests, and in-depth interviews. Vol.324, No. 7337), pp. 573-57

F

Farnsworth, B., 2019. *Facial Action Coding System (FACS) - A Visual Guidebook - Imotions*. [online] imotions. Available at: <<https://imotions.com/blog/facial-action-coding-system/>> [Accessed 5 June 2020].

Feder, Y. (2014). *Social Network 301: What is Virality?* [online] LinkedIn.com. Available at: <https://www.linkedin.com/pulse/20140918141439-7859692-social-network-301-what-is-virality> [Accessed 12 Oct. 2016].

Feroz Khan, G. and Vong, S. (2014). Virality over YouTube: an empirical analysis. *Internet Research*, 24(5), pp.629-647.

France, S., Vaghefi, M. and Zhao, H., 2016. Characterizing viral videos: Methodology and applications. *Electronic Commerce Research and Applications*, 19, pp.19-32.

G

Gardner, M. P. (1985). Mood states and consumer behavior: A critical review. *Journal of Consumer Research*, 12, 281 – 300

Guadagno, R., Rempala, D., Murphy, S. and Okdie, B. (2013). What makes a video go viral? An analysis of emotional contagion and Internet memes. *Computers in Human Behavior*, 29(6), pp.2312-2319.

Goel, S., Anderson, A., Hofman, J. and Watts, D. (2015). The Structural Virality of Online Diffusion. *Management Science*, p.150722112809007.

Golan, G. and Zaidner, L., 2008. Creative Strategies in Viral Advertising: An Application of Taylor's Six-Segment Message Strategy Wheel. *Journal of Computer-Mediated Communication*, 13(4), pp.959-972.

Goman, C., 2015. *Why You Can't Fake Your Feelings*. [online] Forbes. Available at: <<https://www.forbes.com/sites/carolkinseygoman/2015/03/17/why-you-cant-fake-your-feelings/#1916ef845314>> [Accessed 29 May 2020].

Goulding, C. (2002). *Grounded theory: A practical guide for management, business and market researchers*. Sage

Gross, J. and Levenson, R. (1993). Emotional suppression: Physiology, self-report, and expressive behaviour. *Journal of Personality & Social Psychology*, 64(6), 970-986.

Gupta, S. Facial emotion recognition in real-time and static images, *2018 2nd International Conference on Inventive Systems and Control (ICISC)*, Coimbatore, 2018, pp. 553-560.

H

Harley, J. M. (2015). Measuring emotions: A survey of cutting-edge methodologies used in computer-based learning environment research. In S. Tettegah & M. Gartmeier (Eds.). *Emotions, Technology, Design, and Learning* (pp. 89-114). London, UK: Academic Press, Elsevier.

Hargittai, E., and Walejko, G. (2008). The participation divide: content creation and sharing in the digital age. *Information, Communication & Society*, 11(2): 239-256.

Harwood, N., Hall, L. and Shinkfield, A. (1999). Recognition of Facial Emotional Expressions From Moving and Static Displays by Individuals with Mental Retardation. *American Journal on Mental Retardation*, 104(3), p.270.

Heath, C., Hindmarsh, J and Luff, P. (2010) *Video in Qualitative Research*. Sage.

Herrero, J. and Meneses, J. (2006). Short web-based versions of the perceived stress (PSS) and Center for Epidemiological Studies-Depression Scales (CESD): A comparison to penicil and paper responses among Internet users. *Computers in Human Behaviour*, 22, pp. 830-846.

Heilman, K. M. (1997). The neurobiology of emotional experience. *Journal of Neuropsychiatry*, 9, 439-448.

Henson, R. K. (2001). Understanding internal consistency reliability estimates: A conceptual primer on coefficient alpha. *Measurement and Evaluation in Counseling and Development*, 34(3), 177-189.

Heuvel, J. (2017). Plutchik's Wheel of Emotions: What is it and How to Use it in Counseling?. [online] Positivepsychologyprogram.com.

Hitchcock, D. (2012). Deductive and inductive: Types of validity, not types of argument.

Ho, J. and Dempsey, M., 2010. Viral marketing: Motivations to forward online content. *Journal of Business Research*, 63(9-10), pp.1000-1006.

Hobbs, T., Gee, R., Ritson, M., Burrows, D., Rogers, C., Woollen, P., Desai, T., Reporters, M., Hammett, E., Barnett, M. and Joy, S. (2017). *How to measure video effectiveness - Marketing Week*. [online] Marketing Week. Available at:

<https://www.marketingweek.com/2017/08/03/measuring-video-effectiveness/> [Accessed 9 Jul. 2018].

Howes, L. (2012). *How To Go Viral On YouTube: The Untold Truth Behind Getting Views*.

[online] Forbes.com. Available at:

<https://www.forbes.com/sites/lewishowes/2012/08/09/how-to-go-viral-on-youtube-the-untold-truth-behind-getting-views/#56862bde6b97>

Hulley, S. B., Cimmings, S. R., Browner, W. S. (2001) *Designing Clinical Research. An Epidemiologic Approach* (2nd edn). London: Lippincott Williams and Wilkins

Hussey, J. and Hussey, R. (1997) *Business Research: A Practical Guide for Undergraduate and Postgraduate Students*. Macmillan, London

I

Izard, C., 1990. Facial expressions and the regulation of emotions. *Journal of Personality and Social Psychology*, 58(3), pp.487-498.

Izawa, M. (2010). What makes viral videos viral? Roles of emotion, impression, utility, and social ties in online sharing behavior. The Johns Hopkins University, Baltimore, MD.

Retrieved from advanced.jhu.edu/media/files/communication/Izawa-ThesisFinal.pdf

J

Jackson, P.L.; Michon, P-M.; Geslin, E.; Carignan, M.; Beaudoin, D. (2015). EEVEE: the empathy-enhancing virtual evolving environment. *Frontiers in Human Neuroscience*, doi:10.3389/fnhum.2015.00112.

Jarboe, G. (2013). *Top 20 Most Shared Video Ads of 2013 | Search Engine Watch*. [online] Searchenginewatch.com. Available at: <https://searchenginewatch.com/sew/study/2308354/top-20-most-shared-video-ads-of-2013> [Accessed 28 Jul. 2016].

Jenkins, J., Oatley, K. and Stein, N.L. (1998). *Human Emotions: A Reader*. Blackwell Publishing

Jiang, L., Miao, Y., Yang, Y., Lan, Z. and G. Hauptman, A. (2014). *Viral Video Style: A Closer Look at Viral Videos on YouTube*. In: *ICMR*. Glasgow: ACM.

Jiang, Y., Xu, B. and Xue, X. (2014). *Predicting Emotions in User-Generated Videos*. In: *The 28th AAAI Conference on Artificial Intelligence*. Quebec.

Jones, K., Libert, K. and Tynski, K. (2016). *The Emotional Combinations That Make Stories Go Viral*. [online] Harvard Business Review. Available at: <https://hbr.org/2016/05/research-the-link-between-feeling-in-control-and-viral-content> [Accessed 27 Jul. 2016].

Jones, M. (2017). *Emotional Engagement Is the Key to Viral Content Marketing - Cox BLUE*. [online] Coxblue.com. Available at: <http://www.coxblue.com/emotional-engagement-is-the-key-to-viral-content-marketing/> [Accessed 27 Mar. 2018].

Jou, B., Bhattacharya, S., & Chang, S. (2014). *Predicting Viewer Perceived Emotions in Animated GIFs*. *MM '14*.

Jurvetson, S., and Draper, T. (1997). *Viral Marketing*. Netscape M-Files.

K

Kaplan, A. and Haenlein, M., 2011. Two hearts in three-quarter time: How to waltz the social media/viral marketing dance. *Business Horizons*, 54(3), pp.253-263.

Keith, S. J. (2001) Evaluating characteristics of patient selection and dropout rates. *Journal of Clinical Psychiatry*, 62 (suppl. 9), 11–14.

Ketelaar, P., Janssen, L., Vergeer, M., van Reijmersdal, E., Crutzen, R. and van 't Riet, J. (2016). The success of viral ads: Social and attitudinal predictors of consumer pass-on behavior on social network sites. *Journal of Business Research*, 69(7), pp.2603-2613

- Kim, M. and Mattila, A. (2010). The impact of mood states and surprise cues on satisfaction. *International Journal of Hospitality Management*, 29(3), pp.432-436.
- Kong, O., Rizoui, M., Wu, S. and Xie, L., 2018. Will This Video Go Viral: Explaining and Predicting the Popularity of Youtube Videos. In: *WWW '18: Companion Proceedings of the The Web Conference 2018*. ACM.
- Krathwohl, D. (1997). *Methods of educational and social science*. Addison- Wesley Longman, In.
- Kuilenberg , H., Wiering, M. and Uyl, M. (2005). A Model Based Method for Automatic Facial Expression Recognition. In: *16th European Conference on Machine Learning*. Porto: Machine Learning: ECML 2005.
- Kura , S. (2012). Qualitative and Quantitative approaches to the study of poverty: Taming the tensions and appreciating the complementarities. *The Qualitative Report 2012*, Vol. 17, No.34, pp. 1-19.

L

- Lagger, C., Lux, M., & Marques, O. (2011). What makes people watch online videos: An exploratory study. *ACM Computers in Entertainment*, (May 7-12). doi:978-1-4503-0268-5/11/05
- Lee, N., J.Broderick, A. and Chamberlain, L. (2006). What is 'neuromarketing'? A discussion and agenda for future research. *International journal of Psychophysiology*, 63.
- Lee, O. (2009). *Camera Misses the Mark on Racial Sensitivity*. [online] Gizmodo. Available at: <https://gizmodo.com/camera-misses-the-mark-on-racial-sensitivity-5256650> [Accessed 5 Mar. 2020].
- Leskovec, J., Adamic, L. and Huberman, B. (2007). The dynamics of viral marketing. *ACM Trans. Web*, 1(1), p.5-es.
- Levenson R. W. (2003). Blood, sweat, and fears: the autonomic architecture of emotion. *Annals of the New York Academy of Sciences*, 1000, 348–366.
- Levenson, R. and Ekman, P. (2002). Difficulty does not account for emotion-specific heart rate changes in the directed facial action task. *Psychophysiol.*, 39(3), pp.397-405.

Levy, B. I. (1984). Research into the psychological meaning of color. *American Journal of Art Therapy*, 23(2), 58–62

Ioannou, S., Raouzaïou, A., Tzouvaras, V., Mailis, T., Karpouzis, K. and Kollias, S. (2005). Emotion recognition through facial expression analysis based on a neurofuzzy network. *Neural Networks*, 18(4), pp.423-435.

Lohr, S. (2018). *Facial Recognition Is Accurate, if You're a White Guy*. [online] Nytimes.com. Available at: <https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html> [Accessed 5 Mar. 2020].

M

Macefield, R. (2009). *Journal of usability studies*, 5(1), pp.34-35.

Malhotra, N. (2007). *Marketing Research- An Applied Orientation*. 5th edition, NJ: Pearson/Prentice-Hal.

Malhotra, N. & Birks, D. (2007). *Marketing Research: An Applied Approach*. Pearson Education Ltd.

Manheim J. & Rich, R. (1995). *Empirical Political Analysis: Research Methods in Political Science*.

Mauss, I. and Robinson, M. (2009). Measures of emotion: A review. *Cognition and Emotion*, 23(2), pp.209-237.

Mauss, I. B., Levenson, R. W., McCarter, L., Wilhelm, F. H., and Gross, J. J. (2005). The tie that binds? Coherence among emotion experience, behavior, and physiology. *Emotion*, 5(2), 175-190

Maxwell, J. A. (1992). Understanding and validity in qualitative research. *Harvard educational review*, Vol. 62, No 3, pp. 279-30.

McLeod, S. A. (2017). Experimental design. www.simplypsychology.org/experimental-designs.html.

McGinley, J. and Friedman, B. (2017). Autonomic specificity in emotion: The induction method matters. *International Journal of Psychophysiology*, 118, pp.48-57.

Mertens, D. (2009). *Research and Evaluation in Education and Psychology: Integrating Diversity With Quantitative, Qualitative, and Mixed Methods*. 3rd Ed. Sage.

Meyers, T. (2019). *Why our facial expressions don't reflect our feelings*. [online] Bbc.com. Available at: <http://www.bbc.com/future/story/20180510-why-our-facial-expressions-dont-reflect-our-feelings> [Accessed 18 Apr. 2019].

Mikalef, P., Giannakos, M. and Pateli, A., 2013. Shopping and Word-of-Mouth Intentions on Social Media. *Journal of theoretical and applied electronic commerce research*, 8(1), pp.5-6.

Mussel, P., Hewig, J., Allen, J., Coles, M. and Miltner, W., 2014. Smiling faces, sometimes they don't tell the truth: Facial expression in the ultimatum game impacts decision making and event-related potentials. *Psychophysiology*, 51(4), pp.358-363.

Mutch, C. (2005). *Doing Educational Research: A Practitioner's Guide to Getting Started*. Wellington: NZCER Press.

Myers, M. D. (2013). *Qualitative research in business and management*. Sage.

N

Nelson-Field, K., Riebe, E. and Newstead, K. (2013). The emotions that drive viral video. *Australasian Marketing Journal (AMJ)*, 21(4), pp.205-211.

Neuman W. L., 2003. *Social research methods: Qualitative and quantitative approach*. 5th ed. Boston: Pearson Education.

Neuman, W. L., 2011. *Social Research Methods: Qualitative And Quantitative Approaches*. 7th ed. Boston: Pearson Education.

Norman, D.A. (2004). *Emotional design: Why we love (or hate) everyday things*. Basic Books: NY

Nudd, T. (2015). *The 20 Most Viral Ads of 2015*. [online] AdWeek. Available at: <http://www.adweek.com/news-gallery/advertising-branding/20-most-viral-ads-2015-168213> [Accessed 28 Jul. 2016].

O

Oates, B. (2006). *Researching information systems and computing*. Los Angeles: Sage.

Oden, N. and Larsson, R. (2011) What makes a marketing campaign a viral success? A descriptive model exploring the mechanisms of viral marketing. [Online] Vol 1 (Issue 1) Available at <<http://www.diva-portal.org/smash/get/diva2:433110/FULLTEXT01.pdf>> [accessed 12 April 2015]

Ortony, A. and Turner, T. (1990). What's basic about basic emotions?. *Psychological Review*, 97(3), pp.315-331.

P

Patel, M., Doku, V. and Tennakoon, L., 2003. Challenges in recruitment of research participants. *Advances in Psychiatric Treatment*, 9(3), pp.229-238.

Peled, N., Bitan, M., Keshet, J. and Kraus, S., 2014. Predicting Human Strategic Decisions Using Facial Expressions. Tel Aviv: Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence.

Peterson, J., 2014. *How Defining Virality Reveals The Truth About Viral Content*. [online] The Scripted Blog. Available at: <<https://www.scripted.com/content-marketing/viral-content-definition>> [Accessed 10 June 2020].

Petrie, H. and Precious, J. (2010). Measuring user experience of websites: think aloud protocols and an emotion word prompt list. In: *CHI EA '10 CHI '10 Extended Abstracts on Human Factors in Computing System*. New York: ACM, pp.3673-3678.

Phelps, J., Lewis, R., Mobilio, L., Perry, D. and Raman, N., 2004. Viral Marketing or Electronic Word-of-Mouth Advertising: Examining Consumer Responses and Motivations to Pass Along Email. *Journal of Advertising Research*, 44(4), pp.333-348.

Pfister, T., Li, X., Zhao, G. and Pietikannen, M., 2011. Recognising Spontaneous Facial Micro-expressions. In: *International Conference on computer vision*. Barcelona: IEEE, pp.1449-1456.

Pinto, H, Almeida, J and Goncalves, M Using early view patterns to predict the popularity of youtube videos. In Proceedings of the sixth ACM international conference on Web search and data mining, 2013.

Pittaway, L. (2006). Philosophies in entrepreneurship: a focus on economic theories. *International Journal of Entrepreneurial Behaviour and Research*, Vol. 11 No. 3, pp. 201-221.

Plutchik, R. (1980). A psychoevolutionary theory of emotions. *Social Science Information*, 21(4-5), pp.529-553.

Pope, C. & Mays, N. (2008). *Qualitative research in health care*. John Wiley & Sons.

Porter, J., 2013. *9 Lessons From An \$11M Marketing Campaign*. [online] Moz. Available at: <<https://moz.com/blog/9-lessons-from-11-million-dollar-marketing-campaign>> [Accessed 10 June 2020].

Porter, Lance and Guy J. Golan (2006), "From Subservient Chickens to Brawny Men: A Comparison of Viral Advertising to Television Advertising," *Journal of Interactive Advertising*, 6 (2), 30–38.

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology*, 17(3), 715–734. <https://doi.org/10.1017/S0954579405050340>.

Preece, J., Rogers, Y. and Sharp, H. (2011). *Interaction design*. New York, NY: J. Wiley and Sons.

R

Rasooli, P. (2006). *Knowledge management in call centres*. Luleas University of Technology.

Ramachandran VS (2012). "Microexpression and macroexpression". In Ramachandran VS (ed.). *Encyclopedia of Human Behavior*. 2. Oxford: Elsevier/Academic Press. pp. 173–183.

Reeves, B. and Nass, C. (1996). *The media equation: How people treat computers, television and new media like real people*. CSLI: Stanford.

Rhue, L. (2019). *Understanding the Hidden Bias in Emotion-Reading AIs*. [online] Singularity Hub. Available at: <https://singularityhub.com/2019/01/11/understanding-the-hidden-bias-in-emotion-reading-ais/> [Accessed 5 Mar. 2020].

Richins, M. (1997). Measuring Emotions in the Consumption Experience. *J CONSUM RES*, 24(2), pp.127-146.

Rime, B. (2009). Emotion Elicits the Social Sharing of Emotion: Theory and Empirical Review. *Emotion Review*, 1(1), pp.60-85.

Rime, B., Philippot, P., Boca, S., & Mesquita, B. (1992). Long-lasting cognitive and social consequences of emotion: Social sharing and rumination. In W. Stroebe & M. Hewstone (Eds.), *European review of social psychology* (Vol. 3, p. 225). New York, NY: John Wiley and Sons.

Robinson, M. D., and Clore, G. L. (2002). Episodic and semantic knowledge in emotional self report: Evidence for two judgment processes. *Journal of Personality and Social Psychology*, 83(1), 198-215

Rosenthal, R., & Rosnow, R. (1991). *Essentials of behavioral research: Methods and data analysis*. New York: McGraw-Hill.

Roy, S. S. (2011). Exploring the propensity to share product information on social networks (Masters). School of Journalism and Mass Communication, The University of Minnesota, Minnesota. Retrieved from http://conservancy.umn.edu/bitstream/117151/1/Sen%20Roy_Sahana_August2011.pdf.

Rovenpor, D. and Gonzales, j., 2015. *Replicability In Psychological Science Challenges, Opportunities, And How To Stay Up-To-Date.*. American Psychological Association.

Russell, J. (1994). Is there universal recognition of emotion from facial expressions? A review of the cross-cultural studies. *Psychological Bulletin*, 115(1), pp.102-141.

Russell, C. J., & Bobko, P. (1992). Moderated regression analysis and Likert scales: too coarse for comfort. *The Journal of applied psychology*, 77(3), 336-342

Rusting, C. L., & DeHart, T. (2000). Retrieving positive memories to regulate negative mood: Consequences for mood-congruent memory. *Journal of Personality and Social Psychology*, 78, 737-752.

S

Salkind, N. (2010). *Exploring research*. Upper Saddle River, N.J.: Pearson Prentice Hall.

Salganik, M. J., Dodds, P. S., and Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial culture market. *Science*, 311, 854-856.

Saunders, M., Lewis, P. and Thornhill, A. (2009). *Research methods for business students*. Harlow, England: Prentice Hall.

Sauter, D., LeGuen, O. and Haun, D., 2011. Categorical perception of emotional facial expressions does not require lexical categories. *Emotion*, 11(6), pp.1479-1483.

Sayette, M., Cohn, J., Wertz, J., Perrot, M. and Parrott, D., 2001. A psychometric evaluation of the facial action coding system for assessing spontaneous expressions. *Journal of nonverbal behavior*, 25(3).

Scheepers, D. and Derks, B. (2016). Revisiting social identity theory from a neuroscience perspective. *Current Opinion in Psychology*, 11, pp.74-78.

Sekaran, U. (2000) *Research Methods for Business A Skill Business Approach*. John Wiley & Sons, New York.

Shuttleworth, M. and Wilson, L., 2008. *Qualitative Research Design*. [online] Explorable.com. Available at: <<https://explorable.com/qualitative-research-design>> [Accessed 15 June 2020].

Skiendziel, T., Rösch, A. and Schultheiss, O., 2019. Assessing the convergent validity between the automated emotion recognition software Noldus FaceReader 7 and Facial Action Coding System Scoring. *PLOS ONE*, 14(10), p.e0223905.

Slepian, M. and Carr, E., 2019. Facial expressions of authenticity: Emotion variability increases judgments of trustworthiness and leadership. *Cognition*, 183, pp.82-98.

Sohn, K., Gardner, J. T., and Weaver, J. L. (2013). Viral marketing - More than just a buzzword. *Journal of Applied Business and Economics*, 14(1), 21–42

Southgate, D., Westoby, N. and Page, G. (2010). Creative determinants of viral video viewing. *International Journal of Advertising*, 29(3), p.349.

Stets, J. and Burke, P. (2000). Identity Theory and Social Identity Theory. *Social Psychology Quarterly*, 63(3), p.224.

Szabo ,G. and Huberman,B. Predicting the popularity of online content. *Communication of ACM*, 53(8), 2010

usability: A designers guide. *User Interface Engineering*: North Andover, MA.

T

- Tajfel, H. (1978). The achievement of inter-group differentiation. In H. Tajfel (Ed.), *Differentiation between social groups* (pp. 77–100). London: Academic Press.
- Terzis, V., Moridis, C. and Economides, A. (2011). Measuring instant emotions based on facial expressions during computer-based assessment. *Pers Ubiquit Comput*, 17(1), pp.43-52.
- Thayer, R. E., Newman R., and McClain, T. M. (1994). Self-regulation of mood: Strategies for changing a bad mood, raising energy, and reducing tension. *Journal of Personality and Social Psychology*, 76, 910-925.
- Trepte, S. (2006). Social Identity Theory. In J. Bryant & P. Vorderer (Eds.), *Psychology of entertainment* (pp. 255-271). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.
- Trimble, C. (2015). *Why online video is the future of content marketing*. [online] the Guardian. Available at: <http://www.theguardian.com/small-business-network/2014/jan/14/video-content-marketing-media-online> [Accessed 12 Oct. 2015].
- Tullis, T.S., Fleischman, S., McNulty, M., Cianchette, C., & Bergel, M. (2002). An Empirical Comparison of Lab and Remote Usability Testing of Web Sites.

U

- Uyl, T. and Theuws, H., 2018. *Facereader: New Developments In Facial Expression Analysis | Measuring Behavior 2018*. [online] Measuringbehavior.org. Available at: <https://www.measuringbehavior.org/mb2016/facereader-new-developments-facial-expression-analysis.html> [Accessed 3 June 2020].

W

- Wadsworth, Y., & Epstein, M. (1998). Building in dialogue between consumers and staff in acute mental health services. *Systemic Practice and Action Research*, Vol. 11, No. 4, pp. 353-379.
- Watts, Duncan J. and Jonah Peretti (2007), “Viral Marketing for the Real World,” *Harvard Business Review*, 85 (5), 22–23.
- Wagner, U., Galli, L., Schott, B., Wold, A., van der Schalk, J., Manstead, A., Scherer, K. and Walter, H. (2014). Beautiful friendship: Social sharing of emotions improves subjective feelings and activates the neural reward circuitry. *Social Cognitive and Affective Neuroscience*, 10(6), pp.801-808.

Waltz, C., Strickland, O., & Lenz, E. (2005). *Measurement in nursing and health research*. Springer Publishing Company.

Williams, B. (2014). *Descartes: The project of pure enquiry*. Routledge

Wilson, J. (2002). *Evaluation of human work*. London [u.a.]: Taylor & Francis.

Wilson, J. (2010). *Essentials of Business Research: A Guide to Doing Your Research Project*. SAGE Publication.

Winter, G. (2000). A comparative discussion of the notion of validity in qualitative and quantitative research. *The qualitative report*, Vol. 4, No.3, pp. 4

Wu, Z., Singh, B., Davies, L. and Subrahmanian, V., 2018. Deception Detection in Videos. In: *The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)*. Association for the Advancement of Artificial Intelligence.

Wynd, C., Schmidt, B. & Schaefer, M. (2003). Two quantitative approaches for estimating content validity. *Western Journal of Nursing Research*, Vol. 25, No. 5, pp. 508-518.

Y

Yu, C. and Ko, C. (2017). Applying FaceReader to Recognize Consumer Emotions in Graphic Styles. *Procedia CIRP*, 60, pp.104-109.

Z

Zaman, B. and Shrimpton-Smith, T. (2006). The FaceReader: Measuring instant fun of use. In: *Proceedings of the fourth Nordic Conference on Human-Computer Interaction* pages:457-460. [online] Oslo: ACM Press, pp.457-460.

Zheng, X., Shiomi, M., Minato, T. and Ishiguro, H. (2020). What Kinds of Robot's Touch Will Match Expressed Emotions?. In: *Robotics and automation letters*. Kyoto: IEEE.

APPENDIX

APPENDIX A SHARE THROUGH RATE METRICS

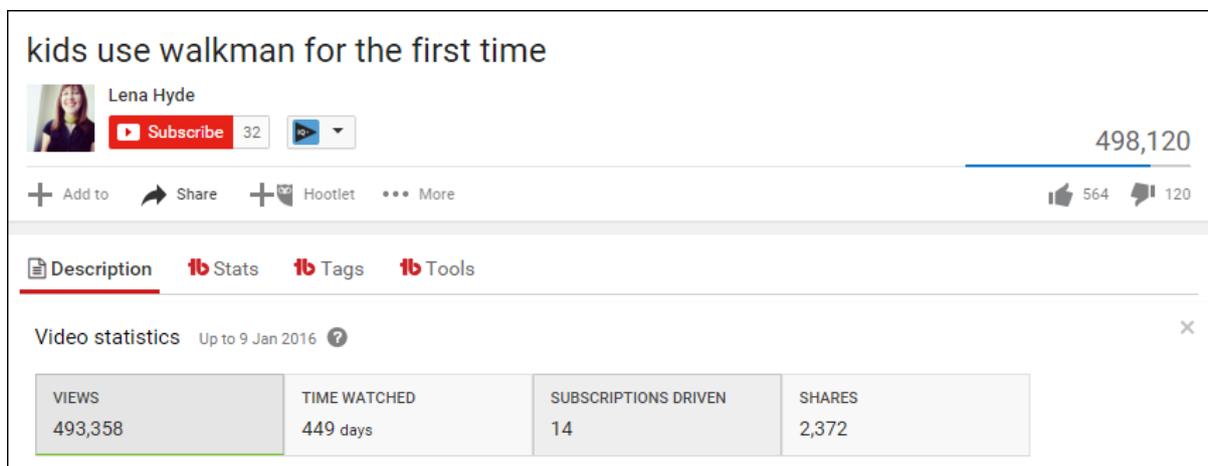
A preliminary study was undertaken to evaluate how the Share Through Rate (STR) formula can be applied in the wider contexts of measuring viral videos. Thus, the following computations were done to provide the needed insight.

METHOD: 100 viral videos were selected from the online viral video database (<http://www.viralviralvideos.com/>). The selected videos were picked based on obtaining the following front-end YouTube Analytics Data: number of views, number of shares, subscriptions driven from views and likes and dislikes.

- **Viral YouTube videos which had opted not to show their YouTube analytics data were rejected**
- **YouTube analytics data was culled between the 29th – 31st of Dec 2015.**
- **The Share Through Rate (STR) was computed for each video as seen below (See 1.0.2.1).**

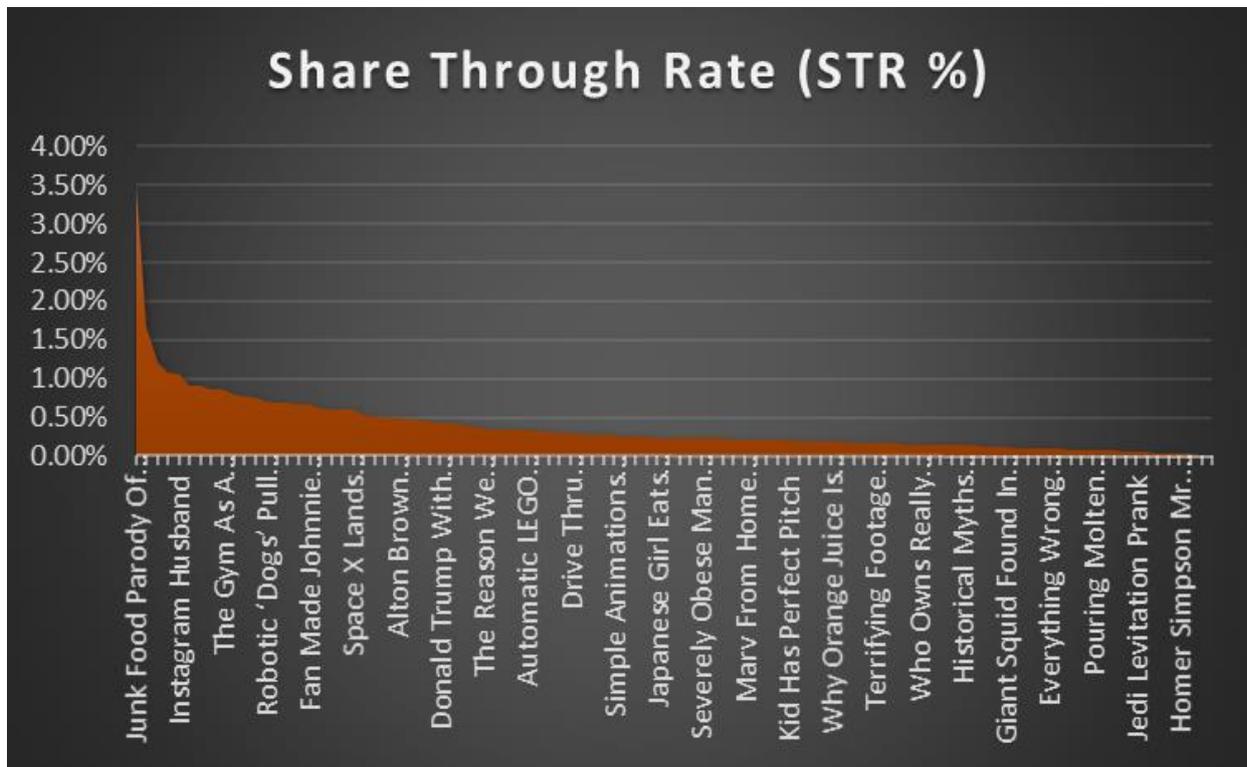
Figure 1.0

Extracted Video Example



- Consequently, each video's STR was collated and depicted in this graph based on a percentile.

Figure 2.0 Total Collated YOUTUBE data (See RAW DATA from Table 1)



From the above graphical chart, a virality threshold was established and categorised as **either Gold, Platinum or Diamond (US)**. Based on this categorisation, a video that has a STR Share Though Rate of more than 0.01% but less than 1% will be considered as **Weakly Trending**, consequently, videos with less than 0.01% will NOT be classified as viral videos.

YouTube	WT	Gold	Platinum	Diamond
Share Through Rate (STR)	0.01-1%.	1% > (25% percentile)	2% > (50% percentile)	3% > (75% percentile)

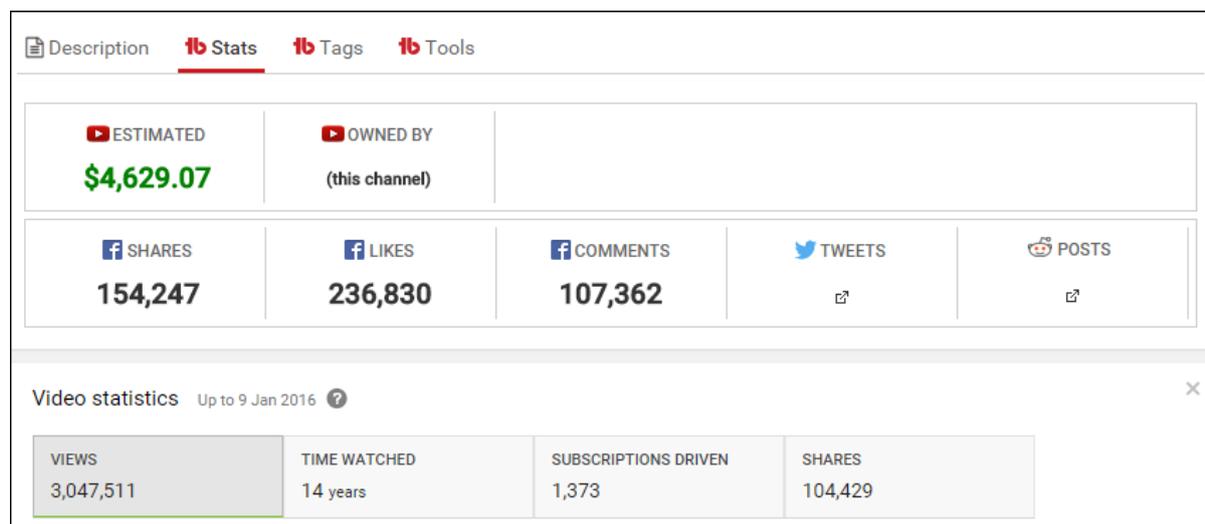
Based from the data gathered, out of a sample of 100 videos only 1 video went **Diamond as seen below with a Share Through Rate of 3.46%**.

Viral Videos	Views	No of		Likes	Dislikes	Total Opinions	Relative likes (Dislikes/Likes)	Share	
		shares	Driven					Through Rate	
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	2,278,554	78,815		1,052	26,573	421	26,994	1.58%	3.46%

Primary Shares and Secondary Shares

Figure 3.0

YouTube Metrics



It is significant to note from the that the Facebook shares (154,247) is more than the shares data on YouTube (104,429), this indicates the occurrence of secondary sharing (social sharing) where users on Facebook shares the video to other people on Facebook. Primary sharing occurs when a user shares a video directly from YouTube to another social platform such as Facebook. The Share Through Rate data was based solely on primary shares.

TABLE 1.0

RAW DATA (SHARE THROUGH RATE)

Viral Videos	Views	No of shares	Share Through Rate (STR)
Kid With Extremely Flexible Neck Will Shock You	2,421,182	5,465	0.23%
Woman Tells Powerful Story About Giving A Piece Of Chocolate During The Holocaust	977,364	11,810	1.21%
Dog Hides Entire Sandwich In His Mouth	128,905	403	0.31%
Color Changing Cake Will Mesmerize You	534,482	716	0.13%
Modern Trailer Of Star Wars: The Empire Strikes Back	1,264,398	5,166	0.41%

Who Owns Really Antarctica	292,302	423	0.14%
Everything Wrong With The Lion King	2,556,907	2,393	0.09%
Budget Remake Of Star Wars: The Force Awakens Trailer	92,298	798	0.86%
Chunk Of Ice Flies Off Of Car On Highway And Smashes The Windshield Another Car	398,673	454	0.11%
Little Kid Loves To Fart	893,129	1,822	0.20%
Giant Squid Found In Japan	2,172,740	2,450	0.11%
Woman Freaks Out In The Best Way After Being Surprised She's A Grandmother	5,840,159	1,042	0.02%
Girl Masters The Violin In Two Years Compilation	1,065,079	2,338	0.22%
Space Debris Over The Past 60 Years	1,254,748	2,676	0.21%
Terrifying Footage Of Family Driving Passed Solimar Fire	108,994	173	0.16%
Misheard Lyrics Of 2015	2,782,568	5,301	0.19%
The Gym As A Wildlife TV Show	7,387,575	63,202	0.86%
Chopping Machine TV Shop commercial	646,443	690	0.11%
Cat Wearing Cone Of Shame Figures Out Drinking Hack	338,571	486	0.14%
Parrot Sick of The Holidays Takes Down Toy Santa Claus	3,744,874	10,001	0.27%
What A World Champion Whistler Sounds Like	603,571	1,004	0.17%
Mama Horse Teaches Baby Horse How To Jump	2,832,254	549	0.02%
Giant Tornado In Holly Springs, Mississippi	566,703	572	0.10%
Marv From Home Alone Is Still Terrified Of Kevin MacCallister	2,297,178	4,837	0.21%
High School Lunch Lady Stuns Cafeteria With Christmas Singing	279,355	250	0.09%
Orangutan Builds Hammock In Zoo Enclosure	742,256	4,390	0.59%
Gorgeous Bruno Mars A Cappella Medley	452,867	1,128	0.25%
Little Girl Has The Cutest And Most Excited Reaction To Star Wars Trailer Ever	479,940	3,286	0.68%
Kitten Trapped In Storm Drain Is Rescued	858,542	2,949	0.34%
Curb Your Enthusiasm Parody Of Steve Harvey's Miss Universe Mishap	641,097	4,024	0.63%

Taco Shop Posts Security Video Of Two Late Night Burglars 'Looking For Tacos'	3,788,692	14,535	0.38%
Robotic 'Dogs' Pull Santa's Sleigh	3,070,807	21,852	0.71%
Space X Lands Falcon 9 Rocket Vertically For First Time	2,062,328	12,190	0.59%
Chris Paul And Aaron Rodgers Perform Trick Shots	6,463,027	9,982	0.15%
Lexus Makes Wheels Out Of Pure Ice	747,295	1,671	0.22%
Cat Demonstrates What Happens When He Climbs Christmas Tree	860,564	1,677	0.19%
Fake Korean Pop Star Prank	3,402,003	6,279	0.18%
Funerals Are a Total Ripoff	1,101,163	1,945	0.18%
Kid Has Perfect Pitch	481,251	949	0.20%
Darth Santa Is Worse Than The Grinch	2,287,888	38,297	1.67%
Guy Flies On \$32,000 Flight To Abu Dhabi	871,280	1,256	0.14%
Devils Fingers Or Octopus Fungus Emerging Is The Creepiest Thing Ever	2,750,533	918	0.03%
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	2,278,554	78,815	3.46%
Doing A Backflip While Breathing Fire Under A Giant Water Balloon	2,465,117	3,816	0.15%
Donald Trump With A Sophisticated British Accent	843,085	3,657	0.43%
Homer Simpson Mr. Plow YouTube Commercial	3,473,937	1,009	0.03%
Pop Stars Sing 'Joy To The World' With James Corden In The Car	2,398,745	6,371	0.27%
Sheriff's Deputy Jumps Onto Moving Semi-Truck To Save Unconscious Driver	157,309	77	0.05%
Macaulay Culkin Returns As A Much Older And Very Neurotic Kevin McCallister	21,798,683	99,336	0.46%
Nerd Makes Real Life Light Saber	4,711,654	12,165	0.26%
Lady Gaga Performs New York, New York	997,684	7,431	0.74%
Deadpool VS Boba Fett Epic Rap Battle	10,028,221	67,818	0.68%
British Weather Report With Star Wars Puns	3,749,961	16,189	0.43%
Hacker Who Built A Self-Driving Car In His Garage	781,936	4,040	0.52%
Little Girl Tries Oculus Rift For First Time	161,997	127	0.08%
Pouring Molten Aluminum Into A Tank Of Water Balls	3,407,861	2,523	0.07%
Three Year Old Adorably Explains Why She Cut Her Hair	1,823,880	1,475	0.08%

Mammoth Stomping Stuff In Slow Motion	1,723,641	972	0.06%
Bad Lip Reading Of The Original Star Wars : A New Hope	5,233,976	46,852	0.90%
Bad Lip Reading Of The Original Star Wars : The Empire Strikes Back	2,171,386	23,510	1.08%
Bad Lip Reading Of The Original Star Wars : Return of the Jedi	1,659,042	15,028	0.91%
Google Year In Search 2015	6,709,406	17,787	0.27%
One Direction Carpools With James Corden	17,501,977	87,110	0.50%
100 Years Of Christmas Toys	497,072	1,165	0.23%
Japanese Girl Eats 100 Pieces Of Bread In One Sitting	1,123,438	2,688	0.24%
The Reason We Think Vitamins Are Good For Us	1,267,366	4,459	0.35%
Simple Animations Battle In Minecraft	11,318,923	29,581	0.26%
Fan Made Johnnie Walker Commercial About Brotherly Love Will Give You Chills	3,381,081	22,436	0.66%
Vanish In A Robe Like Obi Wan Prank	839,123	1,360	0.16%
Motorised Drifting Trike Is Awesome	1,292,447	6,109	0.47%
Commercial A350 Flight Leaving USA Aborts At Last Minute Of Takeoff	1,108,764	800	0.07%
How To Learn Calculus In 20 Seconds	256,431	763	0.30%
John Oliver On Regifting	2,093,069	4,192	0.20%
Why Orange Juice Is Totally Unnatural	683,182	1,209	0.18%
Japanese Police Drone Captures Nearby Drones Using Net	750,183	1,916	0.26%
Beacher Goer Trains Pelicans To Dance	230,159	260	0.11%
Aussie Road Train Driver Demonstrates How To Drive Through Gate	157,132	39	0.02%
Downton Abbey With American Accents Is Bizarre	2,235,940	5,048	0.23%
Everything Wrong With Star Wars Episode I: The Phantom Menace	2,528,115	2,642	0.10%
Kitchen Drawer Blocked By Oven Door Is Fixed In Unexpected Way	284,232	103	0.04%
Michelle Obama Stars In Rap Music Video Encouraging College Enrollment	4,208,551	33,772	0.80%
Drive Thru Christmas Caroling	323,727	944	0.29%
Alton Brown Reviews Dumbest Kitchen Gadgets	3,700,699	18,233	0.49%
Condom Challenge In Super Slow Motion	5,055,248	7,509	0.15%
Automatic LEGO Cookie Icing Machine	90,773	307	0.34%
Elders React To Star Wars The Force Awakens	2,231,528	1,553	0.07%

Historical Myths Many Still Believe	1,718,204	2,326	0.14%
Severely Obese Man Loses Hundreds Of Pounds With Yoga	1,043,877	2,339	0.22%
YouTube Rewind Best Of 2015 Compilation	73,065,696	224,064	0.31%
Quantum Computers Explained	1,398,381	10,796	0.77%
Remote Control Car Tricks	5,497,909	7,933	0.14%
Crystal Pepsi Is Returning Commercial	2,247,404	4,595	0.20%
What It Would Be Like To Visit A Roller Coaster Tycoon Park	2,198,688	7,469	0.34%
Jedi Levitation Prank	818,304	441	0.05%
Instagram Husband	4,709,003	50,205	1.07%
The USAF Band Holiday Flash Mob	1,892,972	8,828	0.47%
Woman Tells Heart Breaking Story About Walmart Cashier Having Worst Day Ever	144,225	763	0.53%
Carrie Fisher Is Hilarious In ABC Interview About Star Wars	1,463,965	5,086	0.35%
Things Get Really Creepy At Christmas Party When Guests Demand To See Santa	1,428,271	8,472	0.59%
Burgers Inspired By The Holidays Will Make You Drool	54,571	371	0.68%

APPENDIX B SIGNIFICANT RESULTS DATA (1a)

Source of computation: GraphPad (Prism 8)

Unpaired *t* test results

P value and statistical significance:

The two-tailed P value equals 0.0190

By conventional criteria, this difference is considered to be statistically significant.

Confidence interval:

The mean of Football Fans (VV1) minus Football Fans(NVV1) equals 0.07300

95% confidence interval of this difference: From 0.01240 to 0.13360

Intermediate values used in calculations:

$t = 2.4080$

$df = 62$

standard error of difference = 0.030

Unpaired t test results

P value and statistical significance:

The two-tailed P value equals 0.0003

By conventional criteria, this difference is considered to be extremely statistically significant.

Confidence interval:

The mean of Non-Football Fans (VV1) minus Non-Football Fans(NVV1) equals 0.06000

95% confidence interval of this difference: From 0.02888 to 0.09112

Intermediate values used in calculations:

$t = 3.8668$

$df = 53$

standard error of difference = 0.016

Unpaired t test results

P value and statistical significance:

The two-tailed P value equals 0.0403

By conventional criteria, this difference is considered to be statistically significant.

Confidence interval:

The mean of Football Fans (VV2) minus Football Fans(NVV2) equals 0.06900

95% confidence interval of this difference: From 0.00316 to 0.13484

Intermediate values used in calculations:

$t = 2.0955$

$df = 61$

standard error of difference = 0.033

Unpaired t test results

P value and statistical significance:

The two-tailed P value equals 0.0280

By conventional criteria, this difference is considered to be statistically significant.

Confidence interval:

The mean of Non-Football Fans (VV2) minus Non-Football Fans(NVV2) equals 0.0500

95% confidence interval of this difference: From 0.0056 to 0.0944

Intermediate values used in calculations:

$t = 2.2625$

$df = 51$

standard error of difference = 0.022

Unpaired t test results

P value and statistical significance:

The two-tailed P value equals 0.0118

By conventional criteria, this difference is considered to be statistically significant.

Confidence interval:

The mean of Female Football Fans (VV1) minus Female Football Fans (NVV1) equals 0.15200

95% confidence interval of this difference: From 0.04034 to 0.26366

Intermediate values used in calculations:

$t = 2.9658$

$df = 12$

standard error of difference = 0.051

Unpaired *t* test results

P value and statistical significance:

The two-tailed P value equals 0.0083

By conventional criteria, this difference is considered to be very statistically significant.

Confidence interval:

The mean of Male Non-Football Fans (VV1) minus Male Non-Football Fans (NVV1) equals 0.1000

95% confidence interval of this difference: From 0.0288 to 0.1712

Intermediate values used in calculations:

$t = 2.9315$

$df = 20$

standard error of difference = 0.034

Unpaired *t* test results

P value and statistical significance:

The two-tailed P value is less than 0.0001

By conventional criteria, this difference is considered to be extremely statistically significant.

Confidence interval:

The mean of Female Football Fans (VV2) minus Female Football Fans (NVV2) equals 0.05000

95% confidence interval of this difference: From 0.03958 to 0.06042

Intermediate values used in calculations:

$t = 10.4583$

$df = 12$

standard error of difference = 0.005

Unpaired *t* test results

P value and statistical significance:

The two-tailed P value equals 0.0106

By conventional criteria, this difference is considered to be statistically significant.

Confidence interval:

The mean of Female Non-Football Fans (VV2) minus Female NonFootball Fans (NVV2) equals

-0.05100

95% confidence interval of this difference: From -0.08916 to -0.01284

Intermediate values used in calculations:

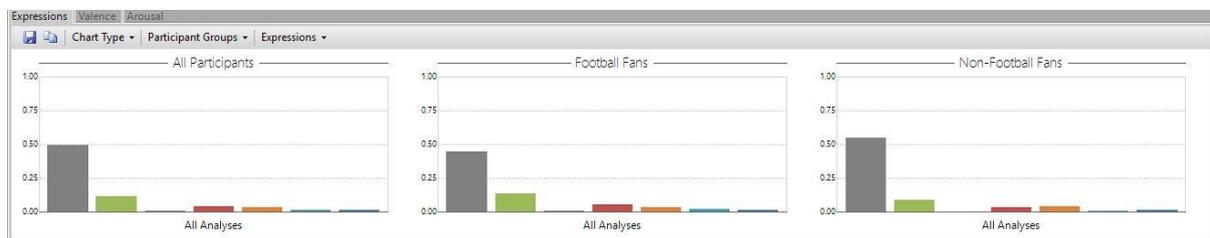
$t = 2.7333$

$df = 29$

standard error of difference = 0.019

APPENDIX C FACE READER ORIGINAL DATA

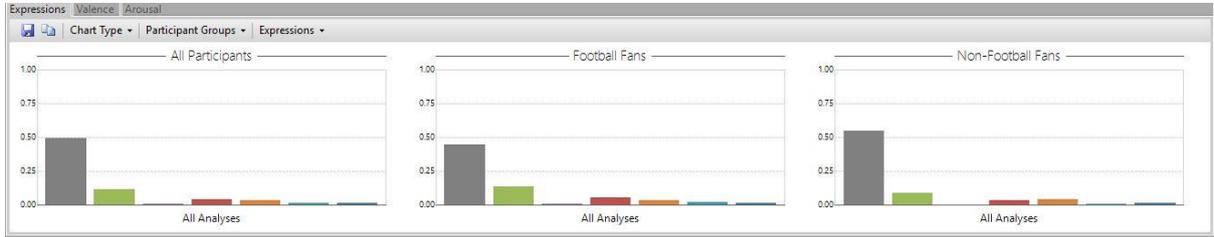
VIRAL VIDEO 1



		Football Fans														(N = 31)			
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	31	0.451	0.199	0.141	0.170	0.011	0.016	0.056	0.154	0.034	0.066	0.022	0.070	0.019	0.032	0.044	0.255	0.340	0.136

		Non-Football Fans														(N = 27)			
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	27	0.551	0.238	0.091	0.117	0.005	0.008	0.035	0.098	0.045	0.113	0.012	0.030	0.019	0.032	0.028	0.163	0.333	0.074

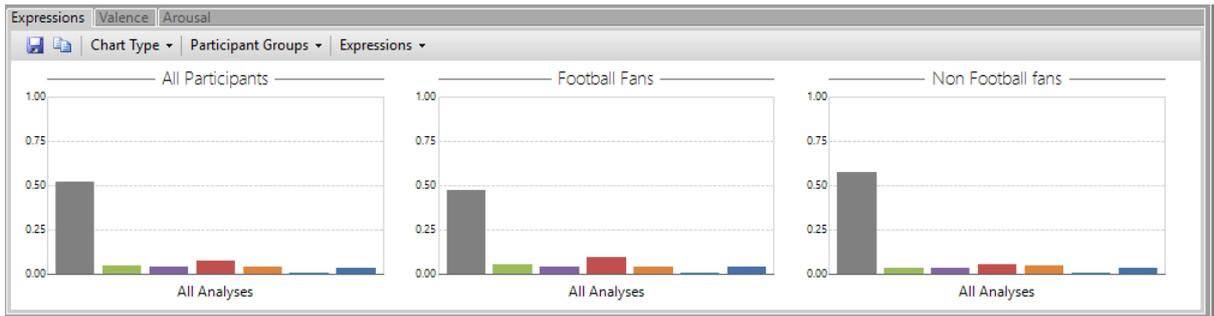
VIRAL VIDEO 2



		Football Fans														(N = 31)			
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	31	0.451	0.199	0.141	0.170	0.011	0.016	0.056	0.154	0.034	0.066	0.022	0.070	0.019	0.032	0.044	0.255	0.340	0.136

		Non-Football Fans														(N = 27)			
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	27	0.551	0.238	0.091	0.117	0.005	0.008	0.035	0.098	0.045	0.113	0.012	0.030	0.019	0.032	0.028	0.163	0.333	0.074

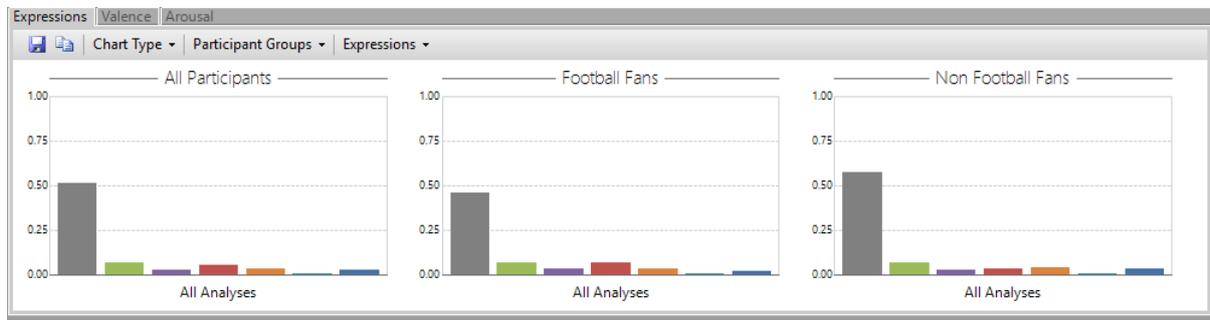
NON - VIRAL VIDEO 1



Football Fans		(N = 32)																	
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	31	0.475	0.217	0.054	0.069	0.046	0.126	0.099	0.189	0.040	0.089	0.007	0.010	0.041	0.075	-0.122	0.238	0.325	0.101

Non Football fans		(N = 27)																	
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	27	0.580	0.240	0.040	0.059	0.034	0.104	0.058	0.117	0.048	0.072	0.012	0.033	0.038	0.098	-0.085	0.204	0.305	0.097

NON - VIRAL VIDEO 2



Football Fans		(N = 32)																	
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	31	0.461	0.214	0.072	0.075	0.034	0.073	0.074	0.143	0.036	0.054	0.013	0.023	0.022	0.033	-0.056	0.180	0.312	0.090

Non Football Fans		(N = 26)																	
Stimulus/Event Marker	N	Neutral		Happy		Sad		Angry		Surprised		Scared		Disgusted		Valence		Arousal	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
All Analyses	26	0.578	0.199	0.072	0.095	0.032	0.076	0.036	0.078	0.043	0.095	0.010	0.023	0.037	0.090	-0.028	0.187	0.281	0.089