The Emotional Impact of Drone Warfare on the Ground

Surname Name: Quaglia Sofia

Student Number: 21206563

School of Politics and International Relations

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Summary

The present research sets out to answer the question "What is the emotional impact of automated warfare on civilians?". This research will centre on the case of the drone war waged by the United States against Pakistan between 2004 and 2018 to highlight the psychological effects of automated warfare on people.

To do this, a brand-new dataset was constructed. The constitutes of tweets linked to individual drone strikes that were written by Pakistani citizens. We then ran sentiment and discrete emotion analysis on the aforementioned dataset.

The latest data casts doubt on the assumption that the majority of Pakistanis see the use of drones as a counterterrorism measure.

According to the research, drones have a detrimental effect on social structures, particularly tribal ones, and this perception of the US as a common adversary among civilians hurts efforts to fight terrorism.

1. Introduction

Previous research on automated warfare focuses on the usefulness of using drones. Drones add a huge strategic advantage to the country that uses them: constant omnipresence over the enemy's territory without endangering the lives of its soldiers (Müller, 2020). Yet, what about the civilians on whom drones are used? The literature on the role of emotions in conflict shows that emotions play a key role in the decision-making process (i.e., reactions) of the actors taking part in the conflict (Lerner and Keltner, 2000).

The present research sets out to answer the question "What is the emotional impact of automated warfare on civilians?". To shed a light on the emotional impact of automated warfare on civilians this research will focus on the case of the drone war deployed by the U.S. on Pakistan between 2004 and 2018 (Ronald Shaw and Akhter, 2011; Fair, 2012).

The current analysis challenges the presumption that the Pakistani populace views the use of drones as a defensive operation against terrorists (Aslam, 2016). This case is interesting for this research because Pakistan's society is mainly organised by tribes (Federally Administered Tribal Area) (Khan, 2000). The research shows that the impact of drones on the social fabric, especially tribal ones, is devastating and leads civilians to perceive drones (and thus the US) as a common enemy (Yousaf, 2020), to the detriment of the war against terrorism (Johnston and Sarbahi, 2016).

To do this, we created a dataset containing tweets posted by Pakistani civilians on specific dates. After that, we performed sentiment and discrete emotion analysis on the said dataset. Once the hypothesis is tested, we report three main findings. We conclude with a reflection on the implications of our findings in the field of automated warfare.

This research is a novelty to the literature on the emotional impact of warfare. Our attempt to fill the gaps in the present literature consisted of two main steps. firstly, we created a new dataset that focuses on civilians. this was a way to focus on the "raw" reactions civilians had related to specific drone strikes deployed and their casualties. secondly, we applied sentiment analysis to it. this was a way to focus on their emotions.

2. Theory and Expectations

2.1 Introduction to Automated Weapons Systems and Their Use

Modern warfare is utterly alien to the accounts taught in today's history books. From wars waged by the family-men of an empire and crusades in faraway lands with the use of horses and other beasts of burden, to more recent mechanical instruments of destruction in both World Wars, the common denominator of all these conflicts has always been one thing: humankind.

The distance between the armies waging these wars has slowly but surely increased with time. From hand-to-hand combat to artillery fire, the battlefield has continually been expanding (Maas, 2019). The desire of minimizing casualties amongst allies while maximizing them on the enemy front has brought about this reality (Rosendorf, 2020). Now wars are fought in office spaces, human soldiers operate console screens and direct drones from thousands of miles away. They may even step away from the battle for a coffee break or take their work home with them in the evenings. A new kind of warfare never witnessed before (Muller, 2021).

Muller categorizes the widely used and widely discussed "drones" as unmanned combat aerial vehicles (UCAVs) and uninhabited aerial vehicles (UAVs) (2021; Sparrow, 2007). UCAVs can be equipped with surveillance technology, yet as well as this, they can also house deadly arms. Take for example the MQ-9 reaper and the MQ-1 predator, armed with missiles, and classified as lethal weapon systems that can be navigated and controlled from thousands of miles away. These UCAVs are specifically used as “hunter-killer” drones combatting counter-insurgency focusing on and targeting the leaders of terrorist groups as part of the war on terror. (Muller, 2021, also Krishna, 2009, also Sparrow, 2007)

If UCAVs were designed to have humans in the loop, lethal autonomous weapons systems (LAWS) are in direct contrast to this. This is well defined by Rosendorf (2020) (also Sparrow, 2020, Wood, 2020) when they describe such weapons as “killer robots” that have a high probability to be the next revolution on the modern battlefield. LAWS place humans out of the loop entirely which fundamentally means that they can detect and select targets that weren’t previously defined, identified or verified by a human.

From the description given of both UCAVs and LAWS, it can be easily discerned that they differ greatly from one another as the presence of a human, or lack thereof can make one feel as if there is a lack of humanity in the LAWS systems in comparison. This gives rise to many questions regarding responsibility and regulations as they entail completely different challenges and dangers both from a political, legal, and even ethical point of view.

One might question how automated and autonomous weapons came to be the bleeding edge of modern warfare. Their widespread acceptance and adoption amongst certain countries and their part in shaping our current and future inter and intra-state wars. In general, the motivations for their use can be broken down into two points of view. The countries that use automated and autonomous weapons and the countries against which such weapons systems are used.

The latter of these is very straightforward. For countries that have automated, and autonomous weapons used against them, it is claimed that such weapons are more precise than humans, therefore they would overall decrease the number of civilian casualties during the span of a war. As Boyle (2015) documents, from an ethical vantage point, the “Obama administration maintained that the US drones' program that was operating during their term in office was humane as it killed relatively few civilians" (Boyle, 2015, pp. 113-114). Wood (2020) also states that autonomous weapons on the battlefield do not have the "issue" of being emotional beings. They act in the most calculated, strategic, and frankly callous manner all the while supposedly eliminating combatting adversaries and saving the lives of non-combatants (Boyle, 2015)

On the other side, there are those countries that have the assets to produce and use automated and autonomous warfare. Why do they decide to use and operate this specific kind of violence on other humans?

Haas and Fischer (2017) summarize quite exhaustively the main reason: in the course of the global war on terror, UCAVs, UAVs and LAWSs gave the Western world the possibility to manage security threats in politically and geographically challenging environments (Riggterink, 2020, also Johnston & Sarbahi, 2016, also Jaeger and Siddique, 2018).

The first reason automated, and autonomous weapons are used has to do with data. Automated and autonomous warfare can collect a huge amount of data, these are key to gathering precious information on the geography of the territory in question, the movements of salient targets as well as the relationships that they could have with allies (Müller, 2020). Computers gather information faster than humans and they can stay on the field for a prolonged amount of time. Unlike manned surveillance flights, which fly for a limited amount of time due to human endurance, drones, for instance, can remain over one territory for far longer, which means a constant feed of data is available, hence a huge knowledge advantage (Boyle, 2015).

Additionally, "weapons systems' algorithms are not susceptible to confirmation bias" (Wood, 2020, p. 8)., as matter-of-fact incoming information should be interpreted by the algorithms only in an already validated way, making the decision process fairer since it can judge all the evidence at its disposal (Wood, 2020).

Secondly, these weapons systems prevent the loss (as well as the loss cost) of soldiers in war, this specific advantage can be called: the distance-proximity advantage. Muller observes that the goal in war was always to achieve more distance to the enemy: automated weapons, i.e., UCAVs and UAVs, permit the soldier to be as close as possible to the target, yet being in the most secure place, i.e., an office cubicle. Soldiers are not at risk when they use these weapons, Muller calls this a “new type of proximity” being exceptionally close to the target, as if they were face to face, while still not being in danger, which also means not experiencing the physical and psychological difficulties of a hands-on fight (Muller, 2020, p. 8)

Wood (2020) also makes an argument in defence of the use of LAWS when a LAWS enters the battlefield, it does not need to preserve its own “life” and it is not going to be scared of what is going to happen. This becomes a powerful skill in life-or-death situations since LAWS will risk their own “lives” to get closer to the target to make sure is the correct and legitimate one before acting. Generally speaking, democracies want to keep casualties to a minimum, to decrease the loss of votes in upcoming elections, which is usually a reason for public opposition to military operations (Rosendorf, 2020).

Finally, the third reason why these countries decide to continue to use automated and possibly autonomous weapons is that overall, they bring the country an “asymmetric” strategic advantage (Maas, 2019, p. 288). As it was shown they allow the countries using them to gather a huge and constant amount of data all without increasing casualties of their armies. These weapons systems keep the enemy at bay by occupying the wanted region persistently. The civilians of said area have to live in the knowledge that they are regularly supervised by invisible automated weapons systems that collect data on their everyday movements and that could strike at any moment, from all that they know (Müller, 2020). This is the power that automated and autonomous weapons systems bring to their user: the power of perpetual surveillance and deterrence by an invisible omnipresence, this is the reason why automated and autonomous weapons systems are perpetrated as a type of violence.

2.2 Different Frameworks to Understand Automated Warfare as a Type of Violence

Until this point, automated and autonomous weapons were defined and understood, as well as the reasons for their use in modern warfare. This section will delve into the different issues that arise from the use of automated and autonomous weapons and with them the different frameworks of study that accompany each one of them.

Firstly, many authors focus their endeavours on understanding whether or not the present regulations and policies are acceptable and or adaptable enough for this new type of warfare or if new ones should be made.

Examining the potential use of autonomous aerial weapons for targeted killing purposes shows how present and future weapons technologies at use, coupled with the current regulations, require a systematic introduction of new international rules and laws (Haas and Fischer, 2017; Rosert and Sauer, 2020). The legal aspect of the administration's drone policy is more dangerous and ethically challenging than the technologies themselves (Boyle, 2015).

Other authors believe that automated weapons systems should be banned as the technology behind them is not controllable by regulation (Krishnan, 2009; Rosendorf, 2020). Banning such systems would also solve the problem arising from the fact that only wealthy countries can invest in automated warfare (Rosendorf, 2020).

Other researchers focus on the possible ethical struggles coming from the use of automated and autonomous weapon systems. They believe the use of automated and autonomous weapons breaches the principles of a just war. Szpak believes that the use of said weapons contravenes the fundamental principles of international humanitarian law. The two basic principles are on one hand the principle of distinction, which states that at all times the civilian population has to be distinguishable from the combatants, and the same goes for civilian objectives and military ones. On the other hand, the principle of proportionality prohibits those attacks that even if they are towards military targets, would expect to cause incidental loss of civilian lives. The civilian loss would be excessive compared to the advantage gained by hitting the target (2019; Wood, 2020).

Another argument is the one of responsibility: when using automated and autonomous weapons systems, and in general in automated warfare as a type of violence, there is no space for responsibility and since being held responsible is a necessary condition for fighting a just war deploying such systems is just unethical (Sparrow, 2007).

Nevertheless, some authors propose some solutions to the problem of responsibility. If one of these weapon systems makes a serious error someone or something must be held accountable. This could be done based on social prestige (Champagne and Tonkens, 2013): accordingly, a person of enough high standards i.e., a President, could accept accountability for the action of an autonomous weapons system even when they are not causally linked to those actions (for instance they were not the programmer or the officer commander). Another possibility is holding accountable who is operating and deploying automated and autonomous weapons systems for the mistakes and misjudgements that may occur Häyry, 2020).

The research and frameworks focus mainly on the side of those countries that own and use automated and autonomous weapons; and that because of the advantage they provide, decide to perpetrate automated warfare as a type of violence. There is a lack of understanding of how automated and autonomous weapons systems affect the civilian populations that they are deployed on, thus more research is needed in this area. Focusing on the victims of this new sort of political violence could shed new light on the debate over automated warfare. This is why this research focuses on the emotional impact of automated warfare and automated weapon systems on the ground.

2.3 Emotions Matter: The Role of Emotions in Conflict

Why are emotions important and why do they matter in a conflict scenario?

Humans have a wide range of emotions, many of which are intrinsic. Some think that facial expressions reflecting basic human emotions are universal, even among nations that have never met (Ekman and Friesen, 2003; Ekman, 2005). Other research, on the other hand, claims that although there are some universal emotions, language and culture have various and significant effects on people (Elfenbein and Ambady, 1994; Russell, 1994). Emotions have evolved to increase a species' reproductive fitness, according to evolutionary biologists and psychologists, since they are triggers for high-value activity. Fear, for example, triggers the fight-or-flight response.

According to some social psychologists, certain societal beliefs, and collective memories regarding the character of the opponent, the in-group, the history, and the current status of the conflict, distort society members' perspectives and prevent them from finding prospects for peace. However, these cognitive obstacles only represent a portion of the picture (Halperin, 2016). According to the research, emotions are strong, pervasive, predictable, occasionally detrimental, and occasionally advantageous drivers of decision-making. Important patterns can be observed in the methods through which emotions affect judgments and decisions across a variety of domains (Lerner et al., 2015). How can certain emotions affect how we judge different things?

The emotion-imbued choice (EIC) (Lerner et al., 2015) is a model (*Figure 1. The emotion-imbued choice (EIC)*) examines how people make decisions based on their emotions. The EIC model believes that the decision-maker is faced with a one-time decision between predetermined possibilities, with no opportunity to seek further information or options. The model terminates when a decision is made, and it excludes actual (as opposed to expected) events and feelings that occur as a result of that decision.

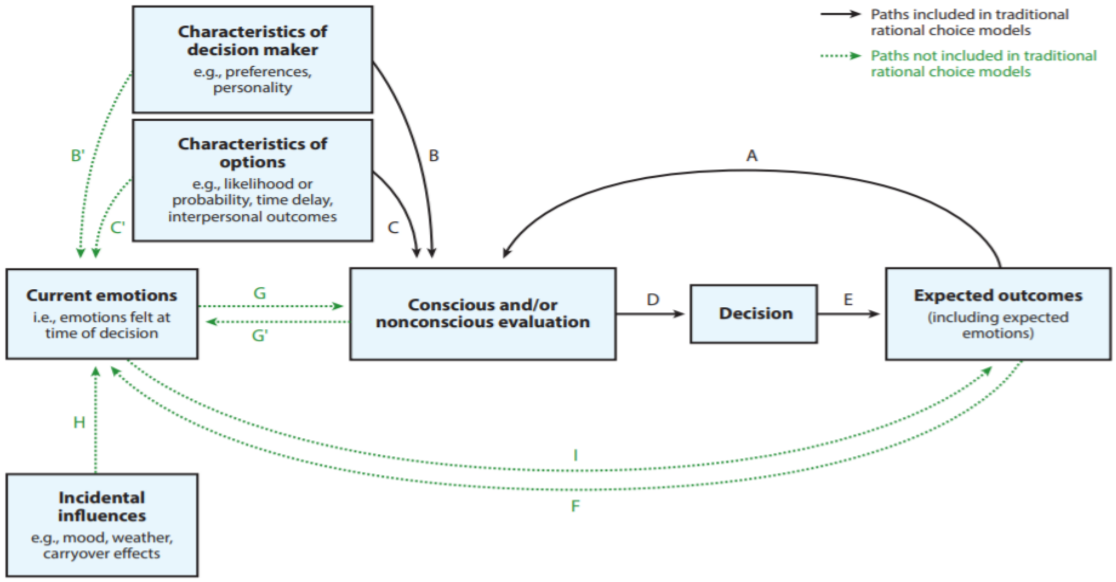

Figure 2. The emotion-imbued choice (EIC) (Lerner et al., 2015)

From the model, it can be understood that emotions influence decisions by changing the content of thoughts and the depth (i.e., how much is that thought valuable and important to a person), which informs the person on whether or not they should act upon that thought or not (Lerner et al., 2015). The interplay among the cognitive and motivational mechanisms activated by each emotion determines whether a particular feeling eventually enhances or degrades a particular judgment or choice (Lerner et al., 2015).

Emotions can have distinct valence[1] and appraisals[2]: every emotion is characterized by a propensity to maintain the cognitive-appraisal features of the feeling while encountering unfamiliar events and things (Lerner and Keltner, 2010). Joy, sadness, anger, fear, disgust, and surprise are the six primary emotions (Ekman, 1992). Plutchik posits an eight-emotions theory. Ekman's six, as well as trust and anticipation, are among them. Plutchik uses a wheel to organize and correlate emotions to each other (*Figure 2. Plutchik's Wheel of Emotions*). The radius represents the intensity of the emotion; the closer it is to the centre, the more intense it becomes.

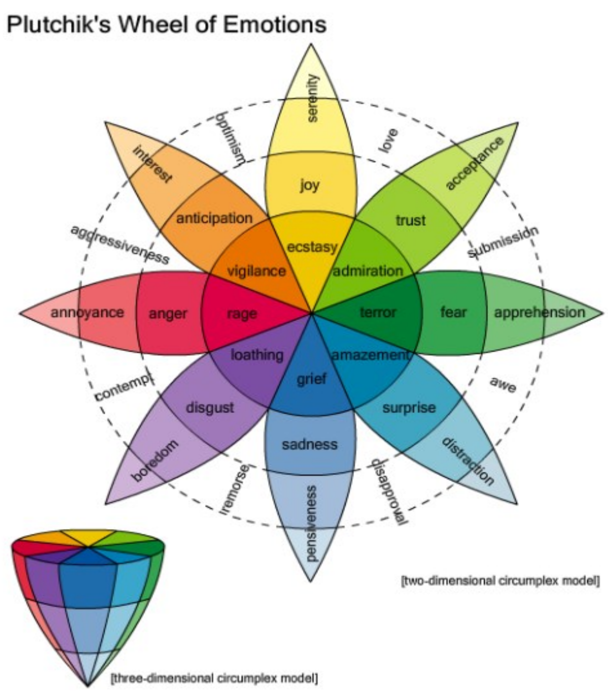

Figure 3. Plutchik's Wheel of Emotions (Mohammad & Turney, 2012)

[1] Valence is the affective quality referring to the intrinsic attractiveness/"good"-ness (positive valence) or averseness/"bad"-ness (negative valence) of an event, object, or situation.

[2] Appraisal theory is the theory in psychology that emotions are extracted from our evaluations (appraisals or estimates) of events that cause specific reactions in different people. Essentially, our appraisal of a situation causes an emotional, or affective, response that is going to be based on that appraisal.

The eight primary emotions, according to Plutchik, constitute four opposing pairs: joy–sadness, anger–fear, trust–disgust, and anticipation–surprise (1980; Mohammad & Turney, 2012).

After understanding how emotions relate to the decision-making process, and how these interrelate. Now is the time to comprehend why this is important when it comes to conflict and war environments where multiple actors, with diversified roles, are at play. Is it possible that defining the role of discrete emotions in conflict and conflict resolution could provide a broad framework for creating targeted conflict resolution interventions?

Pearlman argues that fear, sadness, and shame all encourage gloomy appraisals, risk aversion, and a lack of control (2013). Such depressing feelings drive people to seek security and accept political circumstances, the subsequent result of a "fight-or-flight" response, even if they contravene dignity norms. Anger, joy, and pride, on the other hand, encourage positive judgments, risk acceptance, and emotions of personal efficacy. Such empowering emotions inspire people to prioritize dignity and boost their willingness to engage in resistance, even if it puts their safety in jeopardy. When instrumentality and morals provide contradictory solutions to the question of whether to resign or rebel, emotions can push people in one direction or the other (Pearlman, 2013).

This is essential when it comes to studying the roles and positions of the different actors in a conflict. It can be expected to always find two main actors in a conflict, the establishment actor, and the resistance actor. The establishment actor is the legitimate power holder of the said state, whereas the resistance actor is a political actor that isn't in control of a sovereign state.

An interesting study in which this theory is applied is carried out by Dornschneider. They examine discrete emotions in the occupied Palestinian territories (resistance actor). The findings add to the body of knowledge on popular resistance by showing the coexistence of anger and fear in the resistance actor. Typically, these emotions are linked to opposing behaviours, such as risk-taking vs. risk-avoiding (2021a). The findings show that risk-taking conduct is based on high levels of general positivity, which is consistent with research tying risk-taking activity to positive emotions. Risk-averse conduct, on the other hand, is based on a lower amount of positive and a higher level of negative. This is also consistent with the research on affective valence, which indicates that negative affect has a negative valence (Dornschneider, 2021a; Pearlman, 2013; Lerner & Keltner, 2001). Based on the literature on emotions in conflict, it is possible to say that it is expected for resistance actors to display predominantly negative emotions. Conversely, establishment actors are more prone to show positive ones (Pearlman, 2013).

Nevertheless, in a conflict situation, there is often another actor that has not been considered by the literature: civilians. Why do civilians' emotions matter and why should they be considered when it comes to studying emotions in conflict? Furthermore, in the context of automated warfare as a specific type of violence, how do civilians feel towards such weapons used upon them?

On the one hand, the literature on automated warfare fails to address and analyse the impact of automated and autonomous weapons systems on civilians. On the other hand, the literature on the role of emotions in conflict misses studying the emotions of civilians, specifically when it comes to the involvement and use of automated and autonomous weapons systems on the battlefield. As a result, the role dynamics discussed in the literature on the role played by emotions in conflicts and in the literature on automated warfare need to deal with an additional layer of complexity: the emotional response of civilians to the use of automated warfare against them.

2.4 The Case of Pakistan

As previously stated, the present research aims to answer the question: "What is the emotional impact of automated warfare on civilians?". To shed a light on the emotional impact of automated warfare on civilians this research will now focus on the case of the drone war deployed by the U.S. on Pakistan between 2004 and 2018.

Studying the emotional impact of the drone war conducted by the US in Pakistan on the Pakistani population is important because the focus on civilians' emotions could explain the civilian's behaviour regarding their support to the Pakistani government, the US, or the terrorist groups.

There is evidence that Pakistani civilians, especially those living in the Federally Administered Tribal Areas (FATA), showed a closer affiliation to the terrorist groups in comparison to the Pakistani government or the US army. This is because of the impact that drone strikes had on the Pakistani societal fabric. Elucidating the emotional impact of drone warfare on the Pakistani population will offer interesting insights into civilian behaviour. Furthermore, it would provide important groundwork for the peace-making and policy-making process.

2.4.1 War against terror

The US's current foreign policy toward Pakistan has been greatly influenced by the terrorist attacks of 2001 in New York and Washington, DC. General Pervez Musharraf, the former president of Pakistan, was asked to determine whether he wanted his nation to support or oppose the United States soon after these attacks (Reid 2006). General Musharraf decided to support the United States government's fight against terrorism.

However, Pakistan's army and supreme intelligence agency came under fire for engaging in a "double game" with the Americans (Jones, 2009). This criticism was made because, while Pakistan claimed to be fighting the war on terrorism, it was also secretly supporting militants who were waging war against American and NATO forces stationed in Afghanistan and signing peace agreements with Taliban-affiliated militants (BBC News 2006; Gall 2008).

This prompted Washington to act independently and adopt its strategy of carrying out unmanned drone strikes in Pakistan's tribal regions, which are formally referred to as the FATA. To undertake targeted killing of the terrorists and terrorist suspects who, according to the United States, were hiding there, a growing number of CIA-led drone strikes were conducted. These missile attacks killed not only the terrorist individuals sought by Washington but also those sought by other countries (Aslam, 2011).

The United States launched its first known drone strike in Pakistan on June 19, 2004, kicking off a secret war that would kill thousands of people. Since that first hit, which killed important Taliban leader Nek Muhammad in South Waziristan, Pakistan's use of drones has been cloaked in secrecy, with the government frequently denying strikes or civilian deaths. President Obama began disclosing information on strikes outside of traditional conflict zones in the final year of his presidency (New America, 2022). Overall, the US Central Intelligence Agency has carried out more than 430 drone strikes since 2004 in the Pakistani region (Shah, 2018). The drones used were armed Predator drones (also known as UAVs). As it was explained previously UAVs are automated weapons (not autonomous), hence commanded by drone operators.

The drone war in Pakistan remained relatively restricted during the Bush administration until 2008 when the administration began to ramp up the frequency of operations. The Obama administration continued to escalate strikes, which peaked in 2010 before gradually declining until 2016 when only three known strikes in Pakistan were carried out by the Obama administration. Under Obama, the US carried out its final drone operation in Pakistan on May 21, 2016, killing then-Taliban commander Mullah Akhtar Mansour in Balochistan. In the last eight months of the administration, there were no strikes.

Donald Trump took office on January 20, 2017, inheriting a drone war in Pakistan that had come to an end. The Trump administration launched its first strike in Pakistan on March 2, breaking a nine-month strike hiatus. The most recent drone strike in Pakistan was on July 4th, 2018, in Tor Tangai, North Waziristan and the declared targeted organization was the Taliban.

Polling data from the Pew Research Global Attitudes Project (2014) show that despite extensive media coverage of the drone operation both within and outside of Pakistan, almost two-thirds of Pakistanis have never even heard of it. Males with greater levels of education and Internet usage are more likely than other groups to be aware of the drone initiative (Fair et al., 2014).

To answer the question of whether or not the drone war against terror was effective or not, the literature compares data on drone strikes in Pakistan that hit terrorist leaders to the data when the target was missed, Riggterink finds that terrorist groups in Pakistan increase the number of counterattacks when the drone hits its target (2020). As per the long- and short-term effect of drones on counterterrorism endeavours: (i) there is no hint on long-term effects but in the short-term effects, UAV strikes seem to support counter-terrorism endeavours in Pakistan (Johnston and Sarbahi, 2016). (ii) In Pakistan, UAV attacks have a substantial influence on terrorism, with data indicating that even failed strikes have a large deterrent effect (Jaeger and Siddique, 2018).

2.4.2 A Protective Mission Against Terrorism, or a Dangerous Invasion with High Collateral Damage?

For a total of 430 drone strikes, under three different administrations, an estimated total of 3.702 people (civilians, unknown, militant) lost their lives under U.S. drone strikes, and 3.1% of those were targeted terrorist leaders (New America, 2022).

The US justified such strikes contending the fact that they were helping Pakistan eliminate terrorism. In a meeting with Pakistani officials, General David Petraeus, the former head of US Central Command stated: ‘We are helping you also by hitting your bad guys.’ (Khan 2008).

Nevertheless, whilst many high-value targets have been eliminated using these strikes, the drone attacks have also killed many civilians (Bergen and Tiedeman 2009, Williams 2010, p. 875). There are two types of drone strikes: (i) signature strikes, and (ii) personality strikes. The latter, (ii) personality strikes, requires the drone operator to develop a high level of certainty about the target's identity and location, this information is gathered by the operator’s observation of patterns and behaviours (Fair et al., 2014). On the other hand, (i) in signature strikes the targets are people whose identities are sometimes unknown but who are thought to be militants connected to terrorist organizations. The US determines that the targets exhibit behaviours that add up to a pre-identified "signature”. These behaviours suggest they might be connected to the Pakistani or Afghan Taliban organization or al-Qaida. Officials from the US administration acknowledge that these people may be innocent civilians because the identification of the target is unknown, even during the operation.

All the above brings into question whether the Pakistani population perceives the US acting upon their territories via means of drones, as a protective mission against terrorism or as a dangerous invasion that fragments the population and comes with way too high collateral damage. Polling data from the Pew Research Global Attitudes Project (2014) show that Pakistanis with lower levels of education, women, and people who see the US as an enemy are more likely to oppose the drone program (Fair et al., 2014).

H1: Pakistani civilians’ response will present more negative sentiment than positive sentiment towards the drone war deployed by the US on Pakistani terror groups.

In Pakistan, the military has a substantial influence over the political process, in contrast to Western democracies (Sheikh, 2008). Politicians have never been able to exert as much control over the nation (Aslam, 2011) the tribal areas of Pakistan are very different and complicated to govern from the rest of the country: FATA is divided into seven tribal agencies spanning 27 244 km2 and, according to the last census in 1998, is home to 3.1 million people (Shaw and Akhter, 2011).

These regions are governed according to a system of tribal norms called *Pashtunwali*. One such custom is called *Badal*, which holds that it is essential to kill anyone who murders one's friends or family. Therefore, when innocent civilians are killed by drone attacks, the victims' (mostly male) family members and friends may decide to join militant groups operating in those regions to exact revenge on the United States and its allies, whom they believe to be deserving of it (Fair, Kaltenthaler and Miller, 2016).

Considering the tribal norms and that since 2004, drone attacks have mainly targeted FATA, particularly the agencies of North and South Waziristan, and their ferocity has only grown under the Obama administration (Shaw and Akhter, 2011), in 2006 nearly 100 per cent of strikes in Pakistan resulted in civilian casualties (Farooq, 2020), it is easy to realise that as a result, one effect of such strikes is the emergence of other adversaries beyond those that were initially vanquished (Nawaz 2008, pp. 544-545; see also Gross 2009, p. 114, see also Aslam, 2011). The main problem is that there were local systems in place to deal with violence between tribes and violence brought into the tribal territories from outside before the disintegration of tribal fabrics (Farooq et al., 2020).

The damage to the social fabric of the society in FATA is apparent in situations such as the "elimination of spies". Since drone attacks must be supported by reliable intelligence, this information is frequently obtained from local human sources, which are then considered "spies" by the militants of the area and have to be executed (Khan, 2011; Roggio 2011). Or again, Pakistan's tribal areas are patriarchal, which entails that the patriarch is responsible for the safety and security of each member of the tribe (Aslam, 2011). Numerous people have been killed as a result of the drone operations, and neither the tribal leaders nor the Pakistani government was able to spare any innocent bystanders. This can result in creating a feeling of alienation for the local people: tribesmen feel threatened by the drones, thus the US, and they end up uniting with the militants in the fight against the foreign enemy (Harrison, 2007; Aslam, 2011).

According to what was said earlier, the drone war deployed by the US on Pakistan had the effect of weakening and disintegrating the societal fabric, especially in the FATA tribal regions. This led to creating a shared perception among the population of Pakistan's civilians: fearing the drones on the one hand and being angry at the US for deploying the drones on the other (Gusterson, 2019).

Based on this, it seems promising to explore such arguments in real-case scenarios. The first scenario introduced discusses drone strikes bashed on the area of North Waziristan between September and December 2010.

These four months are interesting, as a very high number of terrorist targets were hit. As shown in *Table 1. Drone Strikes in September December 2010*, for a total of 461 fatalities, 40 were civilian casualties (including children) and 421 were targets. Adding to this, two high-profile targets were killed respectively at the beginning and the end of the four months. On the 26th of September 2010 Sheikh Al-Fateh, al-Qaeda chief in Pakistan and Afghanistan, was killed in a drone strike. On the 17th of December 2010, Ali Marjan, a Local Lashkar-e-Islam commander deceased for the same cause (Rogers, 2013).

Total Drone Strikes	67
Total Deaths	461
High-Profile Targets	2
Total Targets	421
Children	5
Civilians	35

Table 1. Drone Strikes September December 2010

The numbers show that during this time a very low percentage of casualties occurred, and a very high number of targets were hit. The fact that a high number of terrorist targets have been hit during these four months could be an argument in support of the US and drone warfare (Johnston and Sarbahi, 2016). One might think that Pakistani civilians had a halcyon reaction to the fact that these drone attacks were effective and caused a low civilian death toll. Nevertheless, based on the literature, the expectation is quite the opposite:

H2: Discrete emotions of fear and anger are going to show at high levels in response to drone strike attacks executed between September and December 2010.

As highlighted previously, such a hypothesis is founded on the fact that the impact of drones on the Pakistani population is overall negative. Locals feel endangered by the drones and the US which leads them to bear the weight or even support the militants in the struggle against the foreign enemy (Harrison, 2007; Aslam, 2011).

The second scenario analysed is the comparison between two drone strikes that differ based on the type of people who died. On the 23rd of June 2009, a strike hit on people partaking in a funeral in Makeen, Pakistan: out of a total of 72 deaths, 10 were children, and 62 were civilians. No targets were hit. On the 24th of October 2009, up to 27 militants were killed in a strike on a compound in Damadola, Bajaur Agency (Rogers, 2013).

The reason why this comparison is compelling is that the two drone strikes have completely different effects, one strikes the declared targets in the American war against terrorism, while the other strikes innocent children. At first glance, the expectation one might create is that the emotional reaction of Pakistani civilians is positive towards the death of terrorists and negative towards the death of children and civilians (Ronald Shaw and Akhter, 2011). Nonetheless, based on the argument made earlier, because drone warfare has frayed the social fabric of Pakistan (Farooq et al., 2020), no difference is shown in the reaction civilians have to the first attack, where terrorists die, and the second attack, where children die.

H3: Discrete emotions of fear and anger are going to show comparatively similar levels both in strikes where only civilians were killed and in strikes where only terrorists were killed.

As it is showed above, many scholars suggest that US drone strikes cause backlash by radicalizing Muslim populations on a local, national, and even international level by killing innocent civilians. However, other researchers (Shah, 2018; Riggterink, 2020; Johnston and Sarbahi, 2016; Jaeger and Siddique, 2018) add that data from interviews and surveys highlight the relevance of political and economic grievances, the Pakistani state's selective counterterrorism strategies, indiscriminate repression of the local populace, and militant groups' forced recruitment of youth (Shah, 2018). All of these variables interacted in nuanced ways, but collectively they weakened the tribal structure, which in turn increased the militants' authority on the one hand and the public's mistrust of the Pakistani government on the other (Farooq et al., 2020).

Adding to this, the drone attacks have been crucial in uniting many militant organizations against their common foe, the United States, and its partner Pakistan (Fishman 2010, p. 16); they would not have been as unified in the absence of the drone assaults (Jones 2009, p. 41). From this perspective, it seems that drone attacks have no bearing on the American goal of countering regional terrorism, which is the stated reason for the country's engagement in the area (Ronald Shaw and Akhter, 2011).

3. Research Design

As stated in the previous paragraphs the present research sets out to answer the question “What is the emotional impact of automated warfare on civilians?”. To shed a light on the emotional impact of automated warfare on civilians this research will focus on the case of the drone war deployed by the U.S. on Pakistan between 2004 and 2018.

3.1 Hypothesis and Expectations

To answer such a question, based on the literature review three hypotheses were schemed out:

H1: Pakistani civilians' response will present more negative sentiment than positive sentiment towards the drone war deployed by the US on Pakistani terror groups.

H2: Discrete emotions of fear and anger are going to show at high levels in response to drone strike attacks executed between September and December 2010.

H3: Discrete emotions of fear and anger are going to show comparatively similar levels both in strikes where only civilians were killed and in strikes where only terrorists were killed.

Such hypotheses are all founded on the expectation that the impact of drones on Pakistani civilians is overall negative and that there is no substantial difference in the emotional response that civilians display concerning drone strikes that have casualties and drone strikes that do not.

However, another factor to consider is the positivity bias that, in theory, pertains to every language. Positivity bias refers to the phenomenon when the public evaluates individuals positively even when they have negative evaluations of the group to which that individual belongs (Lavrakas, 2008). Dodds et al. observe that (i) the words of natural human language possess a universal positivity bias, (ii) the estimated emotional content of words is consistent between languages under translation, and (iii) this positivity bias is strongly independent of the frequency of word use (2015).

Even considering the positivity bias as a factor, the expectation remains: the overall sentiment presented in the tweets tweeted in response to drone strikes will be negative and levels of fear and anger are going to be consistent (no matter what their target was) (Dodds et al., 2015).

As it is shown in the literature, the war of drones has the following emotional effects on Pakistani civilians: (i) feeling of alienation that leads to a higher percentage of Pakistani joining the terrorist groups (Harrison, 2007; Aslam, 2011); (ii) feeling threatened by the invisible omnipresence of foreign supremacy (Müller, 2020); and finally (iii) the desegregation of the societal fabric, especially in the FATA regions (Farooq, Lucas and Wolff, 2020). All of this leads to a shared emotional perception in the Pakistani society of fear and anger (Gusterson, 2019). In other words, the assumption made is that civilians do not perceive drones to protect them from terrorist groups, rather Pakistani civilians are against the usage of drones in their national territories (Fair, Kaltenthaler and Miller, 2016).

3.2 Methodology

5.2.1 Python Scraper

For the present research, it was necessary to build a dataset that represented the emotional response of Pakistani civilians concerning drone strikes deployed by the US on Pakistan between 2004 and 2018. Since such dataset did not exist yet it was decided to create a dataset from scratch. Tweeter seemed a good resource since from there it is possible to isolate specific tweets from specific users, locations, topics and DateTime.

To retrieve the streaming data from Twitter a scraper was coded. This was done via means of a "*snscrape"*, which is a scraper for social networking services (JustAnotherArchivist, 2020). First and foremost, TwitterSearchScraper was used to scrape the data and append tweets to a list, here all the details of the wanted tweets were stated and finally after the data frame was created it was saved on a CSV file to import it on R studio (Beck, 2022).

3.2.2 Dataset Description and Data Wrangling

Via means of the Twitter API, it was possible to retrieve 30 000 tweets. The actors who tweeted such tweets are non-governmental Twitter users that tweeted between 15/07/2006 (the earliest date available on Twitter) and 01/12/2018 (the day of the last U.S. drone strike on Pakistan). It is important to note that even though the dataset covers a very extensive period and accordingly most of the responses Pakistani civilians have had in reaction to U.S. drone strikes deployed in the Pakistani region, during the present analysis specific drone strikes will be selected and isolated. This is done to have more case-specific analysis as well as results. All the tweets retrieved are in English; furthermore, only tweets published in the geographic area of Pakistan were scraped. Specifying the geo-localisation of tweets is important as it enables the creation of a dataset as case-specific as possible. In addition to this, making sure that the tweets were published from the Pakistani region makes it more plausible that the users are Pakistani civilians.

The hashtags used to frame the research are the following:

```
(#FATA OR #WARCRIME OR #Taliban OR #CounterTerrorism OR
#burraq OR #survivor OR #strike OR #TerrorMonitor OR #ISIS
OR #US OR #JihadWithoutBorders OR #NorthWaziristan OR
#Kurram OR #GilgitBaltistan OR #terrorists OR #Peshawar OR
#PAKISTAN OR #IS OR #terrorism OR #USA OR #usa OR #Genocide
OR #war OR #PakPoint OR #humanrights OR #drones OR #drone
OR #civilians OR #pakistan OR #dronewar OR #obamafail OR
#IHaveADrone OR #CollateralDamage OR #terror)
```

As said previously the dataset has a total of 30 000 observations. They are organized into four variables: "*Datetime*", "*Tweet Id*", "*Text*", and "*Username*". *Datetime* corresponds to the date and the time the tweet was tweeted. *Tweet Id*s are unique 64-bit unsigned integers, which are based on time, instead of being sequential. The full ID is composed of a timestamp, a worker number, and a sequence number. *Text* is the variable containing the actual corpus of the dataset, they are only written tweets of a maximum of 280 words (there is no observation in the form of either audio or video tweets). Finally, the *username* matches the data information about the Twitter user publishing that specific tweet.

As it is shown in *Figure 3* underneath, the dataset created is very extensive. Here the most frequent fifty words overarching the entire dataset are displayed and it is easily noticeable that civilians' reactions to drone strikes happened in Afghanistan (#afganistan) and Yemen (#yemen) are included as well. This is why the Data wrangling undertook many steps during this study. The dataset had to be clean to make sure that all the tweets present in the dataset were related to our case study.

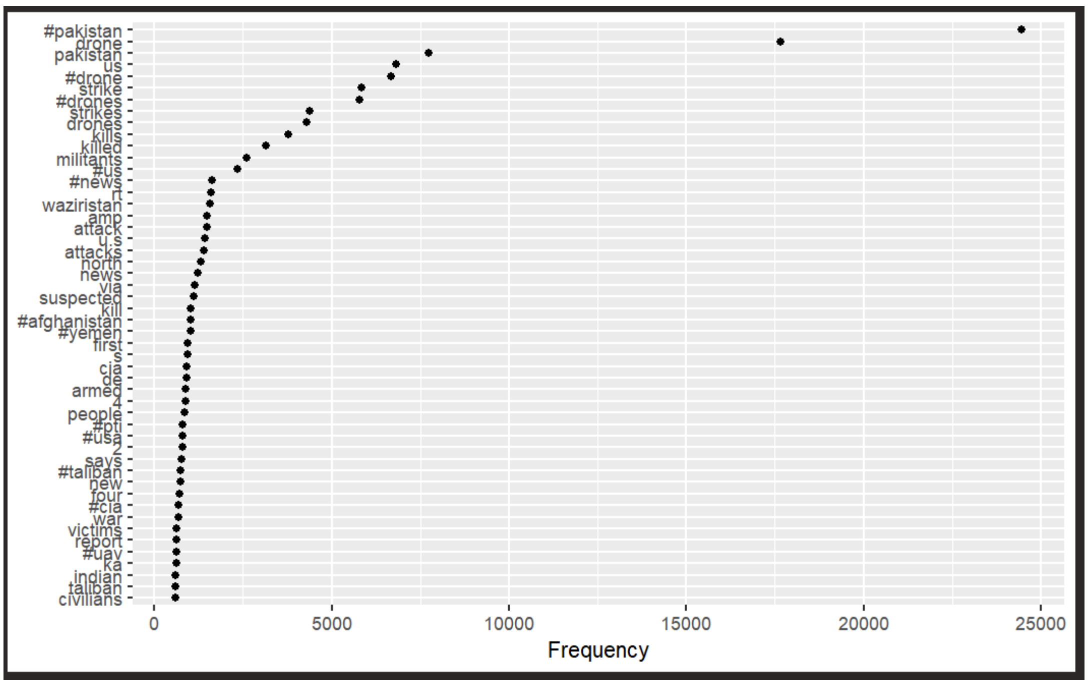

Figure 4. Most Frequent 50 Words, Simple Frequency Analysis Over the Entire Dataset

To start conducting our analysis, it was necessary to pre-process the whole corpus during the "tokenization" phase. To keep our internal validity, we cross-referenced the top sentiment & discreet emotion features in the corpus. Upon closer inspection, we removed some words that did not fit into the category of either "positive" or "negative," "fear," or "trust." This meant that throughout the analysis, we worked with our specific pre-processed version of the corpus, rendered possible thanks to Quanteda's replace function and "dontscore" phrase, to avoid skewing the analysis.

In addition, the corpora had to be wrangled multiple times to match the time frames that we allocated for each major event. This meant that we subset both corpora multiple times and continued with our pre-processing method talked about above.

3.2.3 Dictionaries: Lexicoder-Sentiment-Dictionary and NRC Word-Emotion Association Lexicon and Dictionaries

As aforementioned in the previous paragraphs, the present research aims to test three hypotheses. Since *Hypothesis 1*[3] requires measuring the sentiment (negative or positive) across the corpus in its entirety, it was decided to use the Lexicoder Sentiment Dictionary (LSD) (Young and Soroka, 2012) to test said hypothesis.

The LSD is comprised of words from Roget's Thesaurus, the GI, and the RID. It is a dictionary presenting four keys containing glob-style pattern matches, it is included directly in the Quanteda package for R (Young and Soroka, 2012):

`negative`	2,858-word patterns indicating negative sentiment
`positive`	1,709-word patterns indicating positive sentiment
`neg_positive`	1,721-word patterns indicating a positive word preceded by a negation (used to convey a negative sentiment)
`neg_negative`	2,860-word patterns indicating a negative word preceded by a negation (used to convey positive sentiment

Table 2. Lexicoder Sentiment Dictionary's four keys (Young and Soroka, 2012)

[3] *H1: Pakistani civilians' response will present more negative sentiment than positive sentiment towards the drone war deployed by the US on Pakistani terror groups.*

The LSD is validated in Young and Soroka (2012). They find that in comparison with other dictionaries LSD's capacity to determine the general tone of newspaper articles is overall satisfying. Their evaluation of the LSD's effectiveness is based on what we consider to be crucial tests of external validity: a test to see if the dictionary consistently generates tone codes that match those generated by (expert) human coders, as well as a test to see if it consistently generates these codes more frequently than other dictionaries (Young and Soroka, 2012).

Nevertheless, while many users may find the LSD's non-negation sentiment forms sufficient for sentiment analysis, Young and Soroka (2012) did observe a little but not insignificant improvement in performance when negations were taken into consideration. Therefore, to avoid this inconvenience and be able to test the hypothesis including negations, in the present research the negated positive words were deducted from the positive word count and the negated negative words were deducted from the negative word count if they desire to test this or include the negations (Young and Soroka, 2012).

Hypothesis 2[4] *and 3*[5] are tested via means of the NRC Word-Emotion Association Lexicon. The NRC Emotion Lexicon is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). Mohammad & Turney, the creators of the lexicon chose to use the *Macquarie Thesaurus* as their source and the annotations were manually done via means of crowdsourcing (Mohammad & Turney, 2012) The NRC Word-Emotion Association Lexicon has entries for over 10,000 word-sense pairs. Each entry describes the relationship between a word–sense pair and eight primary emotions. Every one of the 10,170 terms in the vocabulary is also assigned a semantic orientation: positive, negative, or neutral.

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[4] *H2: Discrete emotions of fear and anger are going to show at high levels in response to drone strike attacks executed between September and December 2010.*

[5] *H3: Discrete emotions of fear and anger are going to show comparatively similar levels both in strikes where only civilians were killed and in strikes where only terrorists were killed.*

The lexicon itself was created in English, nevertheless, translations in various languages were provided. To use such lexicon for this research, the licenced version from the official page of the lexicon was downloaded on the local hard drive[6]. The lexicon, therefore, appears as a spreadsheet with a sub-dictionary for each translated language. "Dictionary_English" was transformed into a Quanteda dictionary to allow their use in the Sentiment Analysis.

For this research, the English NRC lexicon, which was used to create the NRC English dictionary, is applied to the corpus of tweets. To validate the sentiment analysis, we followed Chan et al. (2021) approach as follows: 1) we used a suitable sentiment dictionary; 2) we did not assume that the validity and reliability of the dictionary were 'built-in'; 3) we checked for the influence of content length and 4) we did not use multiple dictionaries to test the same statistical hypothesis (Chan et al., 2021).

The NRC lexicon's validity and performance for the English translation of the lexicon is measured by Van Atteveldt et al. (2021), specifically, they test for sentiment positive and negative and discrete emotion of fear and trust. To do so, Van Atteveldt et al. (2021) ran bi-variate correlations between the Dutch and English dictionaries. Most correlations between the tested Dutch dictionaries are weak to moderate, the gold standard for NRC is 0.33. According to Van Atteveldt et al. (2021), the best performance is still attained with trained human or crowd coding and the English version of the NRC lexicon complies with this.

To conclude, the reason in this present research two dictionaries are used is that the three hypotheses to test required a slightly different approach. On one hand, *Hypothesis 1* focuses exclusively on sentiment over the entirety of the dataset: the LSD had a more specific sentiment approach it contemplates negative, positive, negated positive, and negated negative words (Young and Soroka, 2012). On the other hand, the NRC lexicon has a wider focus on discrete emotions (Mohammad & Turney, 2012), which is what is needed to test *Hypotheses 2* & *3*.

[6] https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

3.2.4 Sentiment Analysis

Sentiment analysis is an automated method used to identify affect-laden words from the text (Dornschneider, 2021a). For this study, we first used descriptive statistics to understand the prevalence of positive/negative sentiments and anger/fear emotions throughout our corpora.

We imported the LDS into RStudio to measure the overall sentiment across the entire corpora. Subsequently, we transformed the NRC dictionary into a working English dictionary that we could work with in RStudio. This means that we were able to apply the same NRC measurements for our mixed language corpora, all whilst considering words that should not be scored. Using the summary function (summary) and looking at top features (dfm), we were able to start analysing the data and prepare for a more in-depth analysis involving the plotted distribution of sentiment over a certain period of time. Using the document feature matrix here, we were also able to see what words could not be scored as positive or negative.

Once we were done pre-processing our corpora, we applied context dictionaries to specific instances to see the sentiment-oriented relationship between tweets that were tweeted and published on the platform by Pakistani civilians in response to a specific drone strike, or a drone strike period (i.e., tweets published between the 01/09/2010 and the 31/12/2010). Using Quanteda, we pre-processed our data, applied a context dictionary, filtered that through the language-appropriate NRC dictionary, and turned our results into a plottable data frame. The results seen throughout this paper are realized thanks to the ggplot2 package.

4. Results

We restate the research question: "How does automated combat affect people' emotions?" This research concentrated on the case of the drone war waged by the United States against Pakistan between 2004 and 2018 to offer insight on the emotional effects of automated warfare on civilians. The presumption that the populace of Pakistan views the use of drones as a defensive operation against terrorists is contested (Fair, Kaltenthaler and Miller, 2016). Based on the literature (Fair et al., 2014), it is hypothesized that: Pakistani civilians' response will present more negative sentiment than positive sentiment towards the drone war deployed by the US on Pakistani terror groups. Furthermore, we expect civilians to feel negative emotions such as fear and anger towards the US and contemplate the possibility for said discrete emotion to be predominant (i.e., display high levels) in the discrete emotion analysis. Such assumption is tested on two real case scenarios where it is hypothesized that civilians' negative emotions will be consistent no matter what type of casualties drone strikes have, i.e., high-profile targets, targets, civilians, or children.

Below, *Figure 4,* the printed summary of sentiment analysis on the dataset showing all four keys of sentiment as they pertain to the LSD dictionary.

```
   doc_id              negative        positive        neg_positive  neg_negative
 Length:30001       Min.   :0.00   Min.   :0.0000   Min.   :0     Min.   :0
 Class :character   1st Qu.:0.00   1st Qu.:0.0000   1st Qu.:0     1st Qu.:0
 Mode  :character   Median :1.00   Median :0.0000   Median :0     Median :0
                    Mean   :0.93   Mean   :0.2925   Mean   :0     Mean   :0
                    3rd Qu.:1.00   3rd Qu.:0.0000   3rd Qu.:0     3rd Qu.:0
                    Max.   :8.00   Max.   :5.0000   Max.   :0     Max.   :0
```

Figure 5. Summary Overview of the Dataset Processed with LSD

After gathering the data via means of the python scraper, preliminary sentiment analysis of the dataset was carried out. As the summary shows at first glance, in the dataset containing the Pakistani civilians' responses related to drone strikes deployed by the U.S. in the selected time frame, the mean for positive sentiment is 0.2925 and for negative sentiment 0.93. This indicated that the overall prevalent sentiment is the positive one, this meets our expectation when it comes to *Hypothesis 1*. Based on the literature review civilians will display overall a negative sentiment (and negative emotions) towards the US, as the impact the drone warfare has on the Pakistani population carries way more disruptive outcomes than constructive ones. This even leads them to bear the weight of terrorism in their territory or even support the militants in the struggle against the foreign enemy identifies in the US (Harrison, 2007; Aslam, 2011).

Furthermore, it was decided to test *Hypothesis 1* also concerning the estimated sentiment. To do this, we decided to randomly subset the dataset multiple times and we applied the formula for the estimated sentiment on all the dataset subsets that we got. The ten-dataset subset comprised ten tweets each and the formula applied is suggested by Proksch et al. (2019). In their formula, they assume that general levels of positive and negative sentiment of the corpus are independent of the general levels of sentiment surrounding the corpus's contents. That is, only relative positivity and negativity matter (Proksch et al., 2019). After comparing and evaluating the different results we observed a similar pattern appearing overall in the different subsets. Such a pattern is displayed in *Figure 5*.

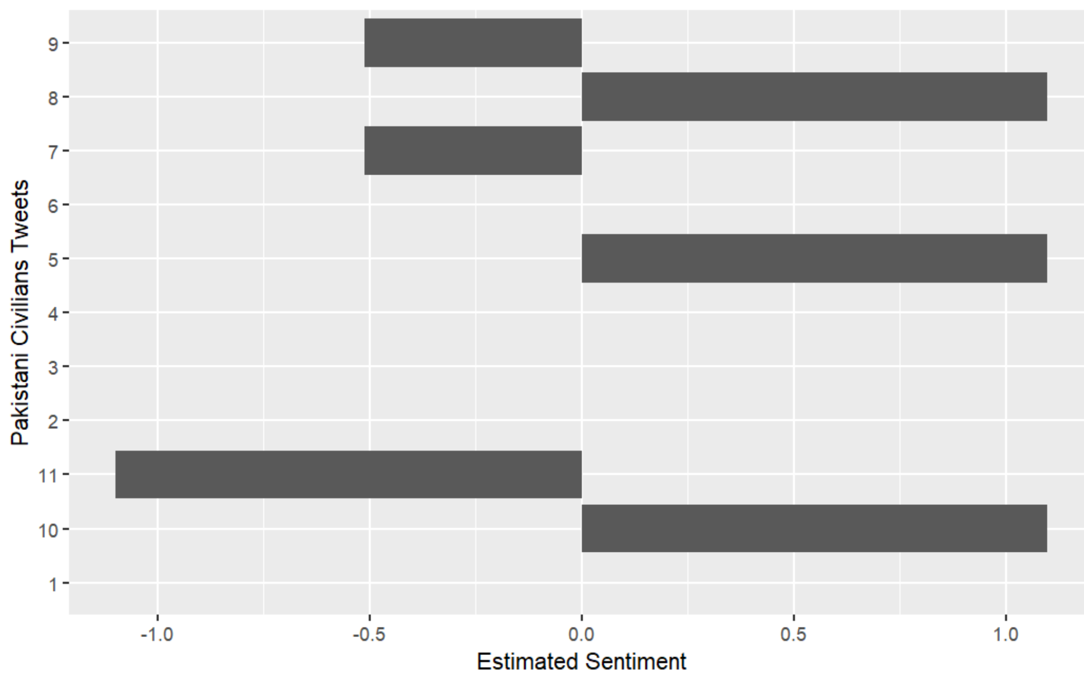

Figure 6. Estimated Average Sentiment of Pakistani Civilians' Tweets

The graph clearly shows that overall positive and negative sentiment, related to the specific corpora that were applied, tends to be balanced. Out of ten speeches, 50 % of them have a predominantly negative sentiment and the rest have a predominantly positive sentiment. In this specific subset (the one displayed in *Figure 5*), it is noticeable that the tweets with a prevalence of positive sentiment score very high, all tweets exceed 1.0 as a score, whereas tweets with a prevalence of negative sentiment fluctuate between – 0.5 and – 1.00.

Intending to test *Hypothesis 2*, it was necessary to isolate the Pakistani civilians' responses to U.S. drone strikes that happened in September and December 2010. As said, this happens to be an interesting period of time as overall 91.32% of the deaths were targets plus two high-profile targets.

Out of the entire dataset comprised of 30 000 tweets, a subset of 5 466 entries was created and sentiment and discrete emotion analysis with the NRC dictionary was run on it. In order to verify the results obtained on the subset, the same sentiment and discrete emotion analysis with the same dictionary were run on the entire dataset. Finally, the results were compared.

Below, *Figure 6*, is the printed summary of the sentiment analysis on the subset containing responses from September to December 2010. Regarding discrete emotions, it can be noticed that anger and fear have the highest mean average. Anger has a mean average of 0.26, whereas fear has a mean average of 0.28. The high score for fear and trust compared to the rest of the emotions meets the expectations drawn from the literature review.

```
   doc_id              anger          anticipation   
 Length:5466        Min.   :0.0000   Min.   :0.00000  
 Class :character   1st Qu.:0.0000   1st Qu.:0.00000  
 Mode  :character   Median :0.0000   Median :0.00000  
                    Mean   :0.2611   Mean   :0.05232  
                    3rd Qu.:0.0000   3rd Qu.:0.00000  
                    Max.   :4.0000   Max.   :3.00000  
   disgust              fear             joy         
 Min.   :0.00000   Min.   :0.0000   Min.   :0.00000  
 1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.00000  
 Median :0.00000   Median :0.0000   Median :0.00000  
 Mean   :0.04299   Mean   :0.2832   Mean   :0.03513  
 3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.00000  
 Max.   :3.00000   Max.   :4.0000   Max.   :2.00000  
   negative          positive        sadness      
 Min.   :0.0000   Min.   :0.000   Min.   :0.0000  
 1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000  
 Median :0.0000   Median :0.000   Median :0.0000  
 Mean   :0.7583   Mean   :0.131   Mean   :0.1411  
 3rd Qu.:2.0000   3rd Qu.:0.000   3rd Qu.:0.0000  
 Max.   :5.0000   Max.   :4.000   Max.   :3.0000  
   surprise            trust       
 Min.   :0.00000   Min.   :0.0000  
 1st Qu.:0.00000   1st Qu.:0.0000  
 Median :0.00000   Median :0.0000  
 Mean   :0.03769   Mean   :0.1045  
 3rd Qu.:0.00000   3rd Qu.:0.0000  
 Max.   :2.00000   Max.   :4.0000  
```

Figure 7. Summary Overview of Subset (September-December 2010) Processed with NRC Dictionary

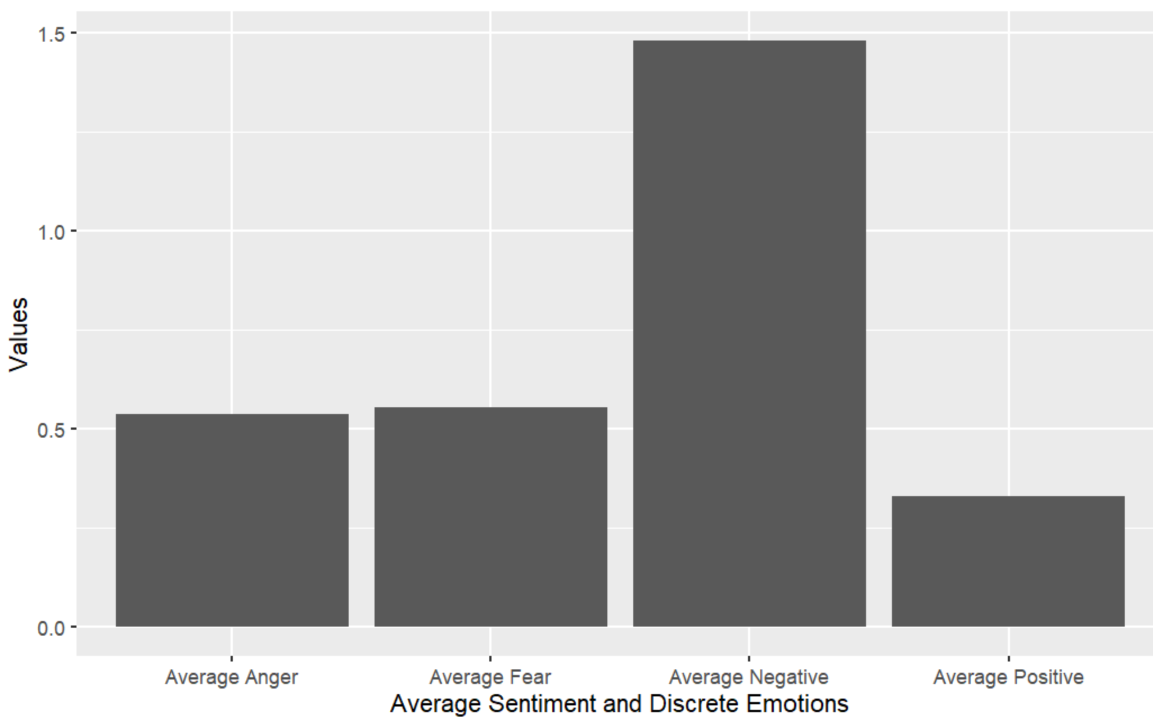

Figure 8. Values for sentiment & anger-fear in Subset (September-December 2010)

By all appearances, the results found in the subset are in line with the results related to the entire dataset. As is shown in *Figure 8*, also overall the entirety of the dataset anger and fear appear to be the discrete emotions with the highest level. The proportions are the same: anger scores 0.53 and fear 0.55. They differ for two centesimal points in both analyses.

```
    doc_id              anger         anticipation
 Length:16188       Min.   :0.000   Min.   :0.0000
 Class :character   1st Qu.:0.000   1st Qu.:0.0000
 Mode  :character   Median :0.000   Median :0.0000
                    Mean   :0.535   Mean   :0.1694
                    3rd Qu.:1.000   3rd Qu.:0.0000
                    Max.   :6.000   Max.   :4.0000
    disgust            fear              joy
 Min.   :0.0000   Min.   :0.0000   Min.   :0.00000
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000
 Median :0.0000   Median :0.0000   Median :0.00000
 Mean   :0.1077   Mean   :0.5534   Mean   :0.08482
 3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:0.00000
 Max.   :3.0000   Max.   :6.0000   Max.   :4.00000
    negative        positive          sadness
 Min.   :0.000   Min.   :0.0000   Min.   :0.0000
 1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:0.0000
 Median :1.000   Median :0.0000   Median :0.0000
 Mean   :1.478   Mean   :0.3298   Mean   :0.2638
 3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:0.0000
 Max.   :7.000   Max.   :6.0000   Max.   :4.0000
    surprise           trust
 Min.   :0.0000   Min.   :0.0000
 1st Qu.:0.0000   1st Qu.:0.0000
 Median :0.0000   Median :0.0000
 Mean   :0.1106   Mean   :0.2763
 3rd Qu.:0.0000   3rd Qu.:0.0000
 Max.   :4.0000   Max.   :5.0000
```

Figure 9. Summary Overview of the Entire Dataset Processed with NRC Dictionary

The fact that a high number of terrorist targets have been hit during these four months could have been an argument in support of the US and drone warfare (Johnston and Sarbahi, 2016). One might think that Pakistani civilians had less of a reaction to the fact that these drone attacks were effective and caused a low civilian death toll. Nevertheless, the results show quite the opposite: *discrete emotions of fear and anger score high levels in response to drone strike attacks executed between September and December 2010.*

As highlighted previously, such a result is corroborated by the fact that the impact of drones on the Pakistani population is overall negative. Locals feel endangered by the drones and the US which leads them to share a common feeling of fear and anger (Harrison, 2007; Aslam, 2011).

Finally, we test *Hypothesis 3*. As explicated previously, the expectation is that discrete emotions of fear and anger are going to show comparatively similar levels both in strikes where only civilians were killed and in strikes where only terrorists were killed. To test this hypothesis, we created two new subsets relevant to the dates of the two strikes. The first dataset is related to the strike that happened on the 23rd of June 2009 (which happens to kill only innocent children and civilians); the tweets scraped cover up to seven days from the day of the strike and it is composed of 24 entries[7]. The same was done for the second dataset which focuses on the week starting the 24th of October 2009 (which hits only people who have been designated as targets in the American war on terrorism) and comprises 80 entries[8]. Since experts hold that news "lives" and circulate for seven days, choosing to scrape all tweets sent up to seven days after the drone strike appeared like an optimal solution.

One could assume that Pakistani residents' emotional responses are good to the deaths of terrorists and bad to the deaths of children and civilians (Ronald Shaw and Akhter, 2011). However, based on the preceding contention that drone warfare has weakened Pakistan's social structure (Farooq et al., 2020), there is no discernible difference between the responses of civilians to the first strike, in which terrorists are killed, and the second attack, in which children are killed.

First and foremost a simple sentiment analysis was run on both datasets. Such analysis was pivotal to detect the levels of sentiment and discrete emotions, specifically anger and fear. The sentiment and discrete emotion analysis, performed on the dataset regarding the tweets surrounding the strike that solely killed innocent civilians and children in Pakistan (June 2009),

[7] It covers from the 23rd to the 30th of June 2009.
[8] It covers from the 24th to the 31st of October 2009.

shows that anger and fear are more present than the other discrete emotions. Anger displays a mean average of 0.45, whereas fear shows a mean of 0.66.

Pertaining to the analysis performed on the subset regarding the tweeted reactions in response to the drone strike deployed a couple of months later (October 2009): the mean average for anger is 0.51 (0.5 centesimal more), while the mean average for fear is 0.62 (0.4 centesimal less). This verifies the expectations of *Hypothesis 3*: between the first attack, in which children and civilians are killed, and the second attack, in which terrorists are murdered, there is no noticeable difference in how Pakistani citizens react.

Curiously, what appears to be different concerns the levels of sadness. The responses regarding the strike deployed on the 23rd of June exhibit a mean average for sadness of 0.5[9], this is an interesting factor when it comes to the comparison with the responses to the strike deployed on the 24th of October where the mean average for sadness is 0.21[10].

The fact that tweets about the death of civilians and children show more sadness than those responding to the death of terrorists is no surprise. The empathetic and emotional movement is more significant for the death of innocents than for the death of terrorists. This could be a factor on which to build further analysis, for example, a study on the actual perception of the Pakistani people of terrorist groups deploying their power in Pakistani territory.

In this research, it has been hypothesized that Pakistani civilians react similarly in terms of fear and anger whether terrorists or innocent civilians and children die because the presence of U.S. drones on Pakistani soil has had devastating effects on the social fabric and this has led to the Pakistani population to identify the U.S. as an enemy, hence fear and anger even towards

[9] *Figure 11* in the Annex.
[10] *Figure 13* in the Annex.

killed terrorists. However, as the data points out, the level of sadness displayed for civilians and children is far more than for terrorists.

To perform targeted sentiment analysis on both subsets we manually organised the subset by date. Every day (and its related tweets) comprises one "micro" subset. When this was done, the variations of four keys (anger, fear, negative, and positive) within the designated week were measured and then plotted.

Figure 9 shows the targeted sentiment analysis with the variation in the mean average of sentiment and discrete emotions of anger and fear related to the strike deployed on the 23rd of June 2009. Within that week only three days (23rd, 24th, and 25th of June) appeared to have tweets concerning the strike.

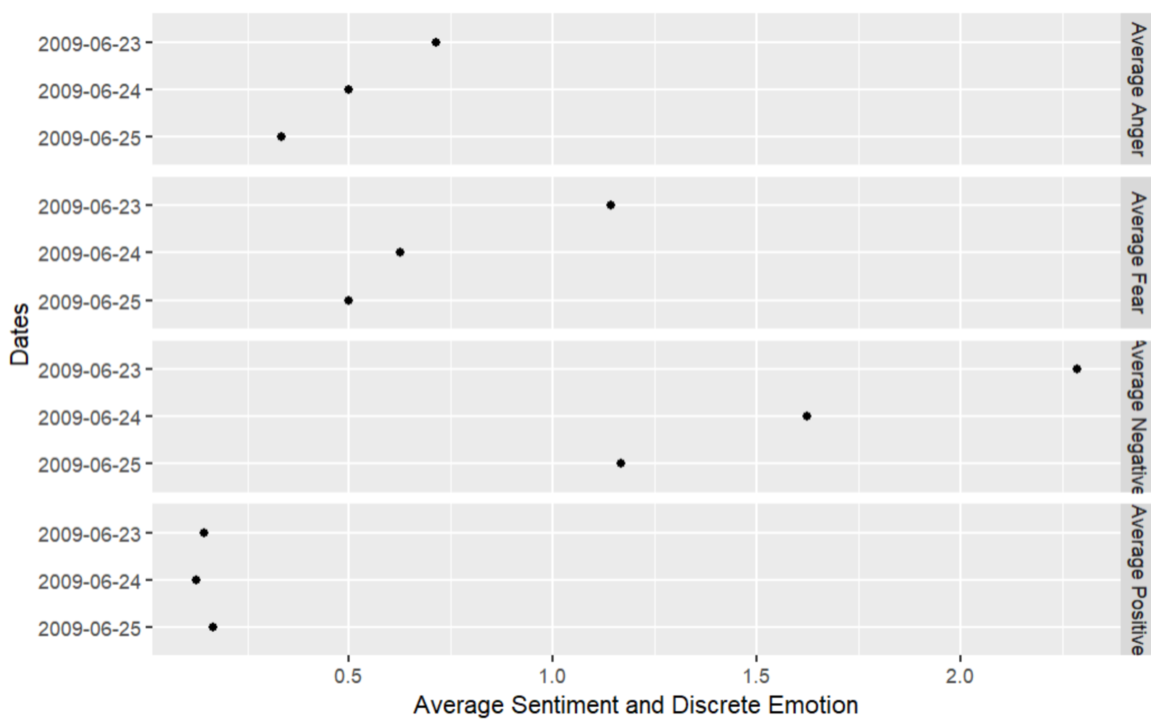

Figure 10. Targeted Sentiment Analysis Strike 23rd June 2009

The variation is coherent with our expectations. On the 23rd (day of the strike) negative sentiment is very high, scoring 2.6, fear is 1.2 and anger 0.7. On the 24th negative sentiment decreases by one unit, scoring 1.6, fear is 0.6 and anger 0.5. On the 25th negative sentiment is now at 1.2, fear at 0.5 and anger at 0.4. Positive sentiment is quite constant alternating between 0.1/0.2. The trend in this dataset is quite apparent, overall, the three days' tweets show very high scores on the first day and then such scores are consistently decreasing.

Figure 10 displays the targeted sentiment analysis with the variation in the mean average of sentiment and distinct emotions of anger and fear associated with the strike launched on the 24th of October 2009. Six days throughout that week—the 24th, 25th, 27th, 28th, 29th, and 30th of October—seemed to have had tweets about the strike.

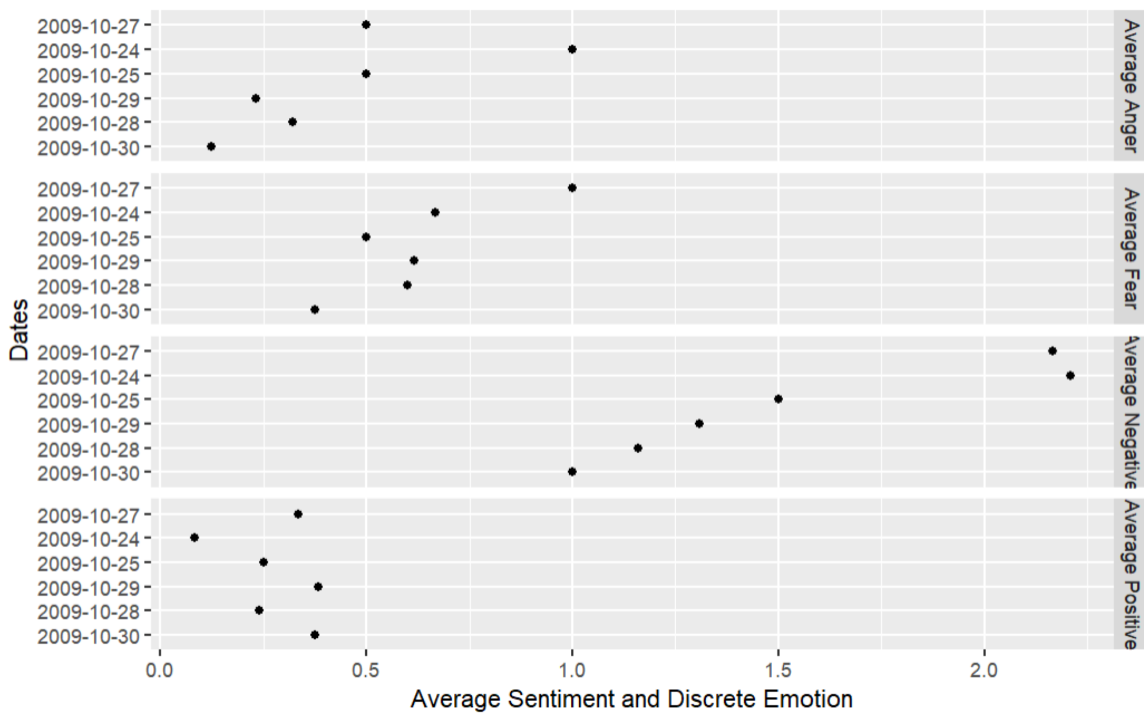

Figure 11. Targeted Sentiment Analysis 24th October 2009

The mean averages of sentiment and discrete emotions of anger and fear follow a very similar trend as the graph in *Figure 9*: anger, fear, and negative sentiment score higher on the first day (24th of October) and consistently decrease on the following days. Positive sentiment presents a constant score throughout the entire week (the score variates between 0.3/0.4). The only difference is that on the 27th there is a peak for fear which goes from 0.5 to 1.0 to then goes back to 0.5. This could be related to the way the information regarding the strike circulated in the news.

Finally, it can be said that also the targeted sentiment analysis proves that the expectations of *Hypothesis 3* were correct: when children and civilians are killed compared to when terrorists are killed, Pakistani civilians' reactions are indistinguishable.

5. Conclusion and Future Work

The current analysis challenges the presumption that the Pakistani populace views the use of drones as a defensive operation against terrorists. “What is the emotional impact of automated warfare on civilians?” is the issue that this study seeks to answer. This study will centre on Pakistan's drone war, which the United States waged against that country between 2004 and 2018, to highlight the emotional effects of automated warfare on people (Johnston and Sarbahi, 2016).

The results of this study show that: (*Result 1*) the emotional reaction Pakistani civilians have on Twitter to drones sent by the U.S. displays overall a higher level of negative sentiment. Furthermore, the results show that (*Results 2 &3*) Pakistani civilians do not change their reaction according to the casualties caused by the attack in question.

Based on the existing literature, it was decided to focus the discrete emotion analysis on two specific emotions: anger and fear. *Hypothesises 2 & 3* were then tested with two case studies. The first situation identified to test the hypothesis presents a drone strike in which 91.32% of terrorist targets and high-profile targets are hit (Rogers, 2013). The second situation identified is a comparison between a drone strike that hits 100% Pakistani civilians and children and a drone strike, a few months later, that only hits legitimate targets (i.e., terrorists) (Rogers, 2013). Both situations show discrete emotions of anger and fear at the same levels, regardless of the victims of the drone strike. An interesting factor to take note of, however, is that there is a difference in the levels of sadness that tweets related to civilians and children being hit exhibit, compared to reactions related to terrorists' targets being killed.

All the results obtained confirm the hypotheses assumed at the beginning of the research. The fact that Pakistani civilians do not show resentment towards terrorists occupying their territories, and nonetheless show discrete emotions of anger and fear towards any drone attacks, regardless of the victims, is dependent on the devastating effect that the U.S.-led drone warfare in Pakistan has on the social fabric, especially in the tribal areas (FATA) (Johnston and Sarbahi, 2016).

In this research, it was decided to use tweets posted by Pakistani civilians in English as a source on which to conduct our investigation. This seemed adequate for the scope of the research, nevertheless, in future studies, it would be ideal to have access to interviews conducted on the Pakistani civilian population (or conduct them first-hand). Such interviews should be in Urdu, and they would constitute the dataset on which sentiment and discrete emotion analysis would be executed. For this, it will be necessary to have an Urdu-speaking person as part of the team and to proceed to verify the dictionary in Urdu (which would be a novelty in the field).

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7. Appendix

```
   doc_id               anger           anticipation
 Length:24          Min.   :0.0000   Min.   :0.00000
 Class :character   1st Qu.:0.0000   1st Qu.:0.00000
 Mode  :character   Median :0.0000   Median :0.00000
                    Mean   :0.4583   Mean   :0.04167
                    3rd Qu.:1.0000   3rd Qu.:0.00000
                    Max.   :2.0000   Max.   :1.00000
   disgust          fear              joy
 Min.   :0.00   Min.   :0.0000   Min.   :0.00000
 1st Qu.:0.00   1st Qu.:0.0000   1st Qu.:0.00000
 Median :0.00   Median :0.0000   Median :0.00000
 Mean   :0.25   Mean   :0.6667   Mean   :0.04167
 3rd Qu.:0.00   3rd Qu.:1.0000   3rd Qu.:0.00000
 Max.   :3.00   Max.   :5.0000   Max.   :1.00000
   negative        positive         sadness       surprise
 Min.   :0.00   Min.   :0.000   Min.   :0.0   Min.   :0
 1st Qu.:0.75   1st Qu.:0.000   1st Qu.:0.0   1st Qu.:0
 Median :1.00   Median :0.000   Median :0.0   Median :0
 Mean   :1.50   Mean   :0.125   Mean   :0.5   Mean   :0
 3rd Qu.:2.25   3rd Qu.:0.000   3rd Qu.:1.0   3rd Qu.:0
 Max.   :6.00   Max.   :1.000   Max.   :4.0   Max.   :0
     trust
 Min.   :0.0000
 1st Qu.:0.0000
 Median :0.0000
 Mean   :0.2917
 3rd Qu.:1.0000
 Max.   :1.0000
```

Figure 12. Summary Analysis on Subset Strike 23rd of June 2009

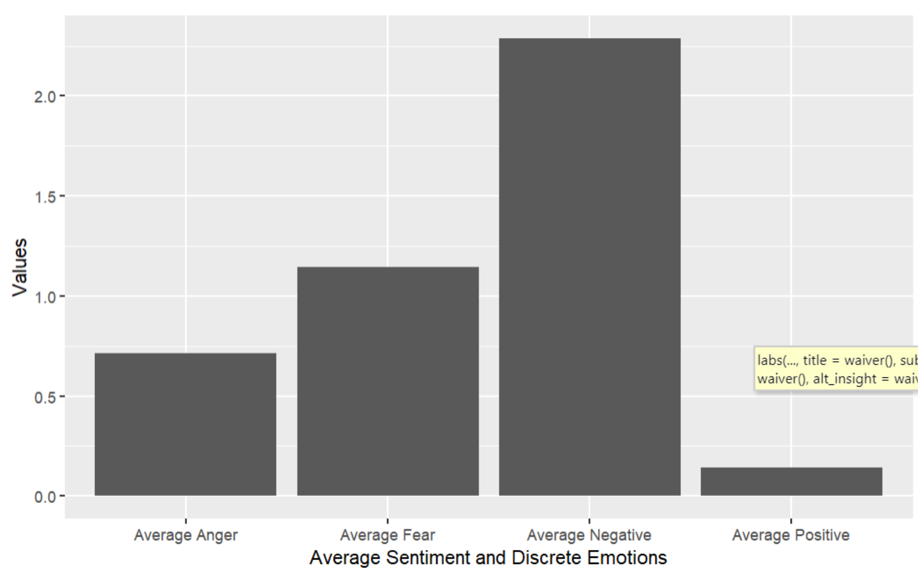

Figure 13. Plot Average Sentiment and Discrete Emotions Anger and Fear on Subset 23rd June 2009

```
   doc_id               anger          anticipation
 Length:80          Min.   :0.0000   Min.   :0.0
 Class :character   1st Qu.:0.0000   1st Qu.:0.0
 Mode  :character   Median :0.0000   Median :0.0
                    Mean   :0.5125   Mean   :0.2
                    3rd Qu.:1.0000   3rd Qu.:0.0
                    Max.   :2.0000   Max.   :2.0
    disgust            fear             joy
 Min.   :0.0000   Min.   :0.000   Min.   :0.00
 1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.00
 Median :0.0000   Median :0.000   Median :0.00
 Mean   :0.1625   Mean   :0.625   Mean   :0.05
 3rd Qu.:0.0000   3rd Qu.:1.000   3rd Qu.:0.00
 Max.   :2.0000   Max.   :3.000   Max.   :1.00
    negative        positive         sadness
 Min.   :0.000   Min.   :0.0000   Min.   :0.0000
 1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:0.0000
 Median :1.000   Median :0.0000   Median :0.0000
 Mean   :1.575   Mean   :0.2375   Mean   :0.2125
 3rd Qu.:2.000   3rd Qu.:0.0000   3rd Qu.:0.0000
 Max.   :5.000   Max.   :2.0000   Max.   :2.0000
    surprise          trust
 Min.   :0.0000   Min.   :0.00
 1st Qu.:0.0000   1st Qu.:0.00
 Median :0.0000   Median :0.00
 Mean   :0.2375   Mean   :0.35
 3rd Qu.:0.0000   3rd Qu.:1.00
 Max.   :2.0000   Max.   :2.00
```

Figure 14. Summary Analysis Subset 24th October 2009

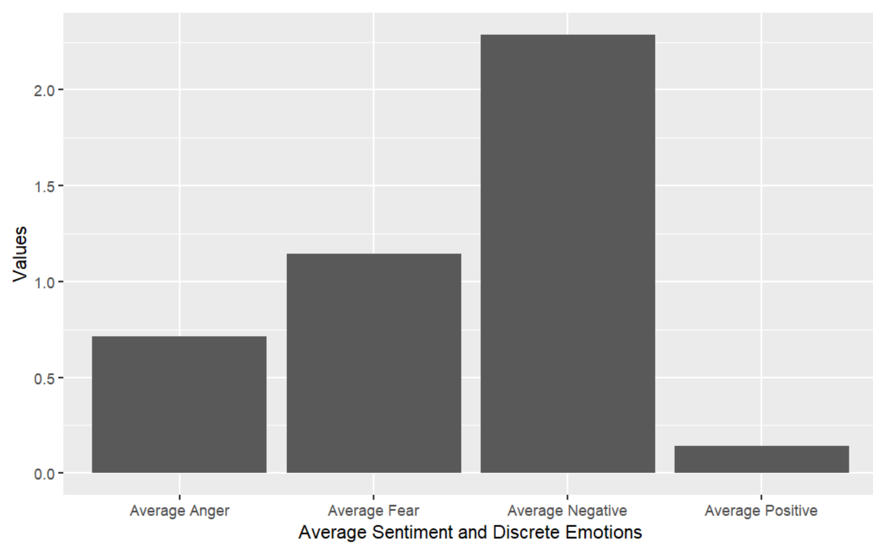

Figure 15. Plot Average Sentiment and Discrete Emotions Anger and Fear on Subset 24th October 2009