# THE PENNSYLVANIA STATE UNIVERSITY SCHREYER HONORS COLLEGE

## DEPARTMENT OF SOCIOLOGY AND CRIMINOLOGY

# THE NATURE AND PREVALENCE OF CYBER-AGGRESSION TARGETING AFRICAN-AMERICANS ON TWITTER

JORDAN LAWSON Spring 2018

A thesis submitted in partial fulfillment of the requirements for baccalaureate degrees in Sociology and Political Science with honors in Sociology

Reviewed and approved\* by the following:

Diane Felmlee Professor of Sociology Thesis Supervisor

Stacy Silver
Associate Professor of Sociology and Human Development and Family Studies
Honors Adviser

\* Signatures are on file in the Schreyer Honors College.

#### **ABSTRACT**

This study investigates and analyzes racially-charged cyber-aggressive tweets targeting African-Americans on the social media platform, Twitter. Through a mixed-methods study using both content-analysis and quantitative methods, I collect and analyze publicly-available data from Twitter (tweets). First, I examine the accessibility of racially-aggressive tweets targeting African-Americans by searching for messages containing four distinct racially-charged terms (co\*n, porch monkey, ni\*\*er, stupid ni\*\*er). Next, I investigate what common negative stereotypical themes are found in racially-aggressive tweets targeting African-Americans, and whether they align with traditional anti-black stereotypes. Additionally, the extent to which racially-aggressive tweets targeting African-Americans spread throughout social networks is considered. Finally, I examine whether there are patterns of defending victims of racist Twitter cyber-aggression, what those patterns may be, and the extent to which users intervene in it. To conduct the study, searches using an open-source, social media importing software are conducted using various terms typically employed to victimize African-Americans. A sample of these 6,437 tweets are then documented, interpreted, and contextualized to address the forthcoming research questions. Digital network visualizations are also included to demonstrate the ways in which these messages can spread throughout social networks. The results show that racist messaging online is indeed a persistent occurrence and is readily accessible to Twitter users. Furthermore, racist messages align with traditional stereotypical themes, and often result in a vicious cycle of online aggression among conversation participants.

# TABLE OF CONTENTS

LIST OF FIGURES	iii
LIST OF TABLES	iv
ACKNOWLEDGEMENTS	V
INTRODUCTION	1
LITERATURE REVIEW	3
Importance of the Study	
Study Details	
Research Questions	
Social Dominance Theory	
Defining Cyber-Aggression	
Accessibility of Racist Cyber-Aggression	8
Themes in Traditional Racist Behavior & Racist Cyber-Aggression	9
Commonly-Held Negative Stereotypes Targeting African-Americans	10
Social Ties in Relation to Cyber- & Non-Cyber-Aggression	
Problems Combating Cyber-Aggression	
Patterns in Defending Victims	
Research Problems	
DATA & METHODS	16
NodeXL	16
The Sample & Data Collection	16
Accessibility & Content Analysis of Cyber-Aggression in Twitter Messages	
Analyzing Resistance to Cyber-Aggression	
Content Analysis of Negative African-American Stereotypes	
Network Analysis of Social Networks Containing Aggressive Twitter Messaging	
Limitations & Strengths	
RESULTS	23
A constitution of Desire Transfer	22
Accessibility of Racist Tweets	
Themes in & Examples of Racist Twitter Messaging	25
Network Visualizations & Examples of Racist Tweets	
Reclaiming	
Intragroup Cyber-Aggression	
Frequency in Victim Defense/Reporting of Aggression	33
DISCUSSION & CONCULSION	36
BIBLIOGRAPHY	40

# LIST OF FIGURES

Figure 1. Example of Edge - Mention/Retweet	20
Figure 2. Example of Edge - No Mention of Other User(s)	20
Figure 3. Example of NodeXL Network Visualization	20
Figure 4. Search Term 1: Co*n - Full Network Visualization	27
Figure 5. Search Term 2: Porch Monkey - Full Network Visualization	27
Figure 6. Search Term 3: Ni**er - Full Network Visualization	28
Figure 7. Search Term 4: Stupid Ni**er - Full Network Visualization	28
Figure 8. Example of Racist Conversation Network - Co*n	29
Figure 9. Example of Racist Conversation Network - Porch Monkey	30
Figure 10. Example of Racist Conversation Network - Ni**er	30
Figure 11. Example of Racist Conversation Network - Stupid Ni**er	30
Figure 12. Example A of 'Reclaiming' Traditionally Racially-Aggressive Terms - Ni**a	31
Figure 13. Example B of 'Reclaiming' Traditionally Racially-Aggressive Terms - Ni**a.	32
Figure 14. Example of Intragroup Cyber-Aggression - Co*n	33
Figure 15. Example of Resistance to Cyber-Aggression - Co*n, Ni**er	34
Figure 16. Example of Resistance to Cyber-Aggression - Stupid Ni**er	35
Figure 17. Example of Resistance to Cyber-Aggression - Ni**er	35

# LIST OF TABLES

Table 1. Twitter Data Collected	24
Table 2. Stereotypical Themes in Racist Twitter Messages	25
Table 3. Examples of Stereotypical Themes in Racist Twitter Messages	26
Table 4. Examples of Racist Tweets	29

## **ACKNOWLEDGEMENTS**

I would like to thank Dr. Diane Felmlee for the endless amount of assistance she provided me with throughout the entire process of creating this thesis. Were it not for her guidance and support, submission of this thesis would not have been possible, and a coherent and comprehensive vision of this project would have been nearly unthinkable.

#### INTRODUCTION

Since the turn of the century, expanded internet communication has resulted in an exponential increase in the number of people who are connected via social media networks. While this adoption of social media has led to a more fluid exchange of opinions, a transformation in the accessibility of news, and has united previously distant populations, it also creates a platform for racially-motivated ideas, especially in the high-speed cyber-world of Twitter (Kowalski et al., 2014).

This research has four main objectives through which I investigate the presence of and responses to racially-motivated cyber-aggression on Twitter, specifically towards African-Americans. First, I explore the accessibility and nature of racism on Twitter. Second, I analyze the common racialized themes present on Twitter and their relation to traditional stereotypes and/or prejudices held against African-Americans. Next, I examine the "seeds of resistance" present in some networks, or, in other words, the ways in which people resist or push back against racially-aggressive messaging on Twitter, if at all. Finally, I visualize illustrations of several networks of racist exchanges on Twitter, as doing so can allow researchers to further understand how far these exchanges can reach throughout the Twitter community.

The guiding research questions I ask include 'how accessible are racially-aggressive tweets directed at African-Americans?', 'what are the common negative stereotypical themes found in racially-aggressive tweets targeting African-Americans and how do they align with traditional anti-black stereotypes?, 'to what extent do racially-aggressive tweets directed at African-Americans spread throughout social networks?', and 'are the patterns of defending

victims of racist Twitter cyber-aggression?' Further, I consider social dominance theory which places a strong emphasis on not just the institutional factors that influence oppressive and prejudiced behavior towards groups, but the individual factors that also contribute to such behavior (Sidanius et al., 2004).

While numerous studies have been conducted on the predictors and impacts of both face-to-face aggression and cyber-aggression (Kowalski et al., 2014; Bauman and Baldasare, 2015; Mishna et al., 2010), research concerning its accessibility and characteristics on social media platforms - Twitter specifically - is in a stage of infancy. Additionally, many commentators, political pundits, and academics, claim there to have been trends that suggest gradual declines in racially-discriminatory and anti-African-American behavior taking place in certain pockets of society (Steeh and Schuman, 1992; Firebaugh and Davis, 1988). However, while that may be the case, the reality could also be that there has not necessarily been a drop in the normalcy of racist and discriminatory behavior so much as a change in that behavior's venue, from a physical environment to one that is cyber – and thus less overt – in nature.

#### LITERATURE REVIEW

## **Importance of the Study**

Bullying, cyberbullying, and cyber-aggression are topics that have been heavily investigated in prior research, especially since the emergence of social media platforms and the accessibility of online communication. A good deal of research exists regarding cyber-aggressive behaviors between adolescents, within schools, and towards both sexes and the LGBTQ population. However, research pertaining to anti-African-American cyber-aggression on social media is in a stage of infancy, and relatively rare (Chatzakou et al., 2017). Some preliminary research investigating racialized populations targeted by more powerful groups on Twitter has been undertaken (Sterner and Felmlee, 2017), but more work needs to be done for it to be better understood.

To be able to better understand the nature and prevalence of racially-motivated, cyberaggressive behavior, foundational research concerning the characteristics and frequency of this
behavior is necessary. Furthermore, this research can assist scholars in determining whether or
not there have been identifiable declines in discriminatory and anti-African-American
stereotypes and sentiment in our society, or if there has simply been a change in the venue for
racially-aggressive behavior from face-to-face interactions to online communications (Steeh and
Schuman, 1992; Firebaugh and Davis, 1988; McConahay, Hardee, & Batts, 1981). On this topic,
Dovidio, Evans, and Tyler (1986) suggest that more contemporary perceptions of race and
ethnicity are less overt and negative and are instead becoming subtler. However, they find that

this may be due to effects of social desirability rather than to changes in respondents' honest attitudes about race.

Finally, from a more tangible and regulatory standpoint, research on racist cyber-aggression can enable social media companies to be more aware of the presence and nature of such behavior, as well as the ever-changing shape of cyber-aggression and cyberbullying in general. Furthermore, it would allow for a greater awareness of the predictors, causes, prevalence, and impact of racial cyber-aggression (Kowalski, et al., 2014), while giving more clarity regarding how to respond to and prevent such destructive behavior on these companies' platforms (Runions, 2013). This is especially important given that it has been found that both victims and aggressors suffer mentally and physically later in life as a result of being involved in aggressive behavior (Nansel et al., 2004).

## **Study Details**

There are four main goals of this research. The first is to document and expose the accessibility and nature of racism on Twitter, using a sample of data derived from Twitter (Smith, et al., 2010). Second, I aim to analyze the common racialized themes present on Twitter and their relationship to traditional stereotypes and prejudices that have been held against African-Americans for generations. Third, this research aims to graphically visualize the social networks that emanate from racially-charged, cyber-aggressive tweets targeting African-Americans to better demonstrate how far throughout online social groups this aggressive messaging can spread. And finally, I will examine the "seeds of resistance" present in some online social interactions. In other words, I question whether people resist and push back against

racially-aggressive messaging and if so, how? Faris and Felmlee (2011) suggest that more effective forms of cyber-aggressive intervention would focus on and highlight bystanders (i.e. those individuals who witness aggressive behavior but choose to not intervene) rather than the bullies and the victims themselves.

#### **Research Questions**

The following research questions will serve as a guide for this investigation.

 $RQ_1$ : How accessible are racially-aggressive tweets targeting African-Americans and are they common?

*RQ*<sub>2</sub>: What are the common negative stereotypical themes found in racially-aggressive tweets targeting African-Americans and do they align with traditional anti-African-American stereotypes?

 $RQ_3$ : To what extent do aggressive tweets targeting African-Americans spread throughout social networks?

RQ4: Are there patterns of defending victims of racist Twitter cyber-aggression?

## **Social Dominance Theory**

Social dominance theory can be effectively related to racially-motivated cyberaggression. A relatively new theory in the fields of sociology and psychology, social dominance theory was formulated by Jim Sidanius and Felicia Pratto and places emphasis on the individual, institutional, and structural factors that influence various methods of oppression based upon group affiliation (Sidanius, et al., 2004). The theory holds that the social and cultural group

membership preferences made by individuals are closely related to the allocation of goods and privileges - such as social standing, economic well-being, and political power - to members of that group. It argues that oppressive social and structural forces between groups are what societies utilize to organize themselves, and that hierarchical constructs are formed to accentuate where groups belong in the social order (Sidanius, Devereux, and Pratto, 1992; Turner and Reynolds, 2003). Social dominance theory contends that all social systems within a society are essentially comprised of a caste structure, with one powerful group occupying the "top spot" and other "negative reference groups" populating below (Sidanius, Devereux, and Pratto, 1992). Furthermore, structural discrimination that is perpetrated by larger institutions such as governments, corporations, or religious bodies influences similar behavior carried out by people on the individual level, creating a vicious cycle of sanctioned and normalized oppression for outgroup members (Sidanius, et al., 2004).

Social dominance theory also suggests that traditional methods of group-based oppression such as sexism, racism, nationalism, or ethnocentrism represent specific actions of a broader trend of people attempting to construct a social hierarchy based upon perceived group statuses (Sidanius, et al., 2004). This argument provides an answer to the question that asks why societies and subgroups within them organize themselves in such a way that creates harmful and destructive discriminatory practices.

Furthermore, this conceptual framework takes a broad focus, one which extends beyond extreme means of intergroup conflict, such as genocide. It also takes a deeper look into the minute and subtle methods of prejudiced, discriminatory, and oppressive behaviors that permeate and shape social interactions between and within cultures on a much more regular basis (Sidanius, et al., 2004). These less obvious harmful actions include disproportionate criminal

sentencing for minorities, sexual harassment towards women, or, in this case, racially-charged cyber-aggression. More specifically, it finds that individuals tend to have preconceived ideologies about outgroup members that validate the discriminatory behaviors they can often practice (Sidanius, et al., 2004). This trend can potentially serve as determinants of microaggressions - the psychological distressers targeting minority populations that serve to construct and sustain power disparities between different groups of people (Sue, Capodilupo, and Holder, 2008). Additionally, ingroup members have been found to act in their own interests more often than do outgroup members, thus perpetuating the validation of discriminatory ideologies by members of more powerful groups (Sidanius, et al., 2004).

Finally, at its most basic level, social dominance theory holds that group-based oppression is a systematic behavior that disproportionately targets outgroup members within societies. Individuals who are part of more powerful social groups wield the power that shapes influential institutions, and their beliefs and behaviors often legitimize their own harmful ideologies and endorse them via action (Sidanius, et al., 2004). The theory suggests that the nature of human social organization emanates from an innate and predisposed drive to separate into groups, and to strive for dominance at the expense of out-group members (Turner and Reynolds, 2003).

Racially-charged cyber-aggression represents a contemporary, modernized form of social inter- and intragroup conflict, a behavior to which social dominance theory can be applied.

Twitter users choose with whom they form their social groups. They choose with whom they want to communicate, and how to go about facilitating those interactions, as in other voluntary social interactions. It can be assumed that their motivations for conducting those online interactions in the ways in which they do - whether aggressive or not - are guided by similar

social forces that dictate their face-to-face interactions with other individuals. I hypothesize that outgroup members, such as African-Americans, are likely to be targeted online by racism. Here, I argue that African-Americans' repressed position in our society's social hierarchy represents one mechanism behind such oppressive actions.

#### **Defining Cyber-Aggression**

To be able to accurately and effectively investigate the prevalence and nature of racially-charged cyber-aggression, it must first be defined and distinguished from other related concepts. While they are often misconstrued as being one in the same, cyber-aggression and cyberbullying are two distinct concepts. While the latter is more commonly used and understood, the former has a much broader definition (Wright and Li, 2013). Cyber-aggression – the concept of main focus in this research – is defined by Felmlee and Faris (2016) as "electronic or online behavior intended to harm another person psychologically or damage his or her reputation." In other words, cyber-aggression is known to be a behavior in which there is a conscious intention to mentally damage or socially attack another individual or group. This term is useful, because the term 'cyberbullying' requires the online behavior to be repeated while also targeting a victim with a less amount of perceived social power or status (Felmlee and Faris, 2016).

## **Accessibility of Racist Cyber-Aggression**

The first goal of this investigation is to begin to document the potentially widespread nature of cyber-aggression targeting African-Americans on Twitter. Because of the platform's recent emergence as a main form of social media engagement, the amount of research that has

been devoted to cyber-aggression on Twitter specifically is relatively underrepresented.

However, other older means of digital communication such as Facebook, Gmail, texting, instant messaging, email, and Myspace have allowed for prior investigation into cyber-aggression more broadly. This prior research can serve as a preview of the nature of such interactions on the much younger medium of Twitter.

In a study conducted using the responses of 788 adolescents, it was found that 17% of respondents reported some sort of association with cyber-aggressive behaviors during a week of reporting, whether the participants in those online interactions were the perpetrators of aggression or the victims (Felmlee and Faris, 2016). Additionally, Wang, Iannotti, and Nansel (2009) found that just under 14% of all youth surveyed (13.6%) reported to have been victimized by aggressive online behavior within the previous two months. However, Mishna et al. (2010) determined that upwards of 49.5% of respondents admitted to having been targeted within the previous three months. While these and other reported rates often vary in both percentages of those victimized and the time frame during which adolescents are asked to consider their online social interactions, they all serve to make one common point: A substantial portion of online users are engaged in some form of victimization and cyber-aggression. However, little research focusing on the victimization and participation of African-Americans in particular has been undertaken.

## Themes in Traditional Racist Behavior & Racist Cyber-Aggression

Another aim of this study is to report whether the themes of racially-charged cyberaggressive behavior align with those used in more traditional, non-electronic communications. Such an investigation may lead to a better understanding of the ways in which methods of communication and prejudice have been altered (or unaltered) since the emergence of online social interactions.

Previous research regarding the everyday difficulties encountered by African-Americans finds that racially-charged instances of intimidation, offensive name-calling, social exclusion, public shaming, and embarrassment are common problems (Allan, Cowie, and Smith, 2009). For example, in a study Moya Bailey coins the term 'misogynoir' to address pop culture's increasing tendency to aggressively target black women in music, specifically (Bailey, 2013). Furthermore, cyber-aggressive behaviors such as aggressive comments, threats, and social isolation are frequent methods of victim ostracization in adolescents and school communities, and tend to be perpetrated by males (Alvarez-Garcia, Barreiro-Collazo, and Nunez, 2017; Li, 2007). This behavior often victimizes minority populations such as LGBTQ individuals, females, and Asians at rates higher than that of whites and men (Felmlee and Faris, 2016; Mouttapa et al., 2004). Here, I hypothesize that the same is the case for African-American populations, another frequent target of racial discrimination.

 $H_1$ : Racially-charged cyber-aggression targeting African-Americans on Twitter will be a frequent occurrence.

## **Commonly-Held Negative Stereotypes Targeting African-Americans**

Racial prejudice is present within American society and there is considerable consistency between individuals holding race-based stereotypes (Katz and Braly, 1935). One 20th century study found that the very mention of certain races elicits emotions within the minds of most

Americans, as well as an acceptance of traditional characteristics associated with those races. African-Americans are often viewed as one of the least-favorable racial groups by Americans as a whole (Katz and Braly, 1935), with negative stereotypical characteristics associated more often with African-Americans, and more positive stereotypical characteristics more often applied to whites (Dovidio, Evans, and Tyler 1986).

Devine and Elliot (1995) conclude that stereotypical images and ideas of African-Americans still permeate American culture, and that the negative views held towards this group are widespread. Furthermore, among respondents in numerous studies, common negative stereotypes regarding African-Americans include the perceptions of them as lazy, stupid, violent, ignorant, and dependent; (Devine and Elliot, 1995; Lapchick, 2000). In another study, researchers asked respondents to associate various races with certain characteristics and timed how long it took those associations to be made. African-Americans were more often and more quickly associated with negative stereotypes than were whites (Gaertner and McLaughlin, 1983). White Americans were evaluated as more ambitious, smart, and clean than their African-American counterparts. Given these findings, I hypothesize that traditional negative stereotypes targeting African-Americans will align with themes of racially-charged cyber-aggression.

 $H_2$ : Traditional anti-African-American stereotypes presenting African-Americans as lazy, unintelligent, violent, and dependent will align with themes of cyber-aggressive messages targeting them on Twitter.

To be able to conceptualize the extent to which racially-charged cyber-aggression spreads through Twitter social networks, an understanding of how aggressive tweets manifest themselves must first be developed. Felmlee and Faris (2016) state that there is substantial evidence to suggest that adolescent cyber-aggression often occurs within individuals established social networks, that is, between friends, mutual friends, or significant others. It has also been suggested that as the size of individuals' social networks grow, so do their chances of becoming involved in cyber-aggressive interactions, whether they are the perpetrators of aggressive behavior, the victims, or a bystander (Wegge et al., 2015).

A broader picture of social communication and aggressive behavior can be established by expanding this consideration past just online interactions. In another study conducted by Felmlee and Faris (2011), however, respondents were found to have been least likely to partake in aggressive face-to-face behavior if they were either some of the most or least socially-engaged individuals in question. In addition, individuals were more likely to victimize targets within their social circles as opposed to those on the outside of them.

Furthermore, Haselager et al. (1998) find that friends within social groups often share similarities in aggressive behaviors. These behaviors have then been observed to influence the process of welcoming more companions into their social group. Subsequently, having close social ties to individuals who are also aggressive is positively related to a person's participation in aggressive behavior (Mouttapa et al., 2004; Warman and Cohen, 2000). Finally, victims of aggression often inhabit relatively smaller and sparser social networks than other individuals, as found by Mouttapa et al. (2004). Victims tend to be seen as 'social outcasts' on the fray of their social surroundings.

This subsection considers the relationship between outgroup members and individuals with less social ties and their experiences with aggression both online and offline. Given that African-Americans are often labeled as racial outgroup members (Jussim, Coleman, and Lerch, 1987), it is reasonable to infer that behavior towards them will follow the pattern of increased and prolonged aggression targeting individuals with less social standing.

## **Problems Combating Cyber-Aggression**

To assess how victims and other actors respond to and potentially push back against aggressive behavior on Twitter, it is first necessary to understand why it may be difficult to do so in the first place. Numerous studies find that one of the most pervasive problems facing institutions and individuals who try to counteract the issue of cyber-aggression is that they simply do not know the identity of the attacker (Li, 2007; Wolak, Mitchell, and Finkelhor, 2007). To compound that problem, both Li (2007) and Mouttapa et al. (2004) suggest that it is also often the case that a fair percentage of victims of cyber-aggression are also aggressors themselves, thus creating a vicious cycle of social interactions and dynamics. Also, Menesini et al. (2003) note that it is often challenging for individuals who have previously taken up aggressive behaviors to justify acting as the defender of another victim in a different interaction. These issues present challenges not only to potential defenders in altercations, but to institutions and scholars trying to better understand how to combat the issue as well.

## **Patterns in Defending Victims**

However, there are also observable examples of people defending victims in social interactions, even though their defense of those victims happens more often in physical interactions, as opposed to those that take place online (Hodges, Malone, and Perry, 1997). As those researchers find, victims of aggressive behavior who have social ties that are socially willing to intervene to defend them are less likely to suffer from victimization in the future. However, Wegge et al. (2015) contend that close online friendships have not been found to increase the level of protection from cyber-aggressors.

Recently, scholars have placed an emphasis on encouraging bystanders to speak out against aggressors and bullies, because they can act as a deterrent to the social reinforcement of aggressors in aggressive interactions (Desmet et al., 2012; Faris and Felmlee, 2014). However, scholars also point out that little research investigates the psychological reasons behind how, why, or when bystanders choose to intervene in cyber-aggressive incidents. By further investigating the patterns of these behaviors of resistance, a more effective means of encouraging such behavior can be established.

Desmet et al. (2012) also contend, however, that adolescents chose to intervene and defend victims of cyber-aggression only under certain circumstances, such as when the aggressors targeted characteristics out of the victim's control (such as race, ethnicity, gender, or appearance), or when aggression is perceived as unnecessarily severe. Additionally, defense of these victims is partly predicated upon the strength of social ties between the victim and defender, the perceived social risk associated with intervening, as well as the defender's assessment of self-efficacy. Desmet et al. (2012) also find that resistance to cyber-aggression by

outside parties can take various forms, and that when individuals come to the aid of victims, those targets are viewed more favorably while the aggressors are faced with animosity.

 $H_3$ : Cyber-aggression targeting African-Americans will go largely undefended.

#### **Research Problems**

This project aims to assess four key factors related to the trend of cyber-aggression targeting African-Americans on Twitter. First, a deeper investigation into the accessibility, severity, and accessibility of cyber-aggression targeting this demographic on Twitter is conducted. This will allow subsequent researchers to better understand the nature of this behavior. Next, common negative stereotypical themes held against African-Americans are examined to determine whether they reflect general themes of aggressive tweets targeting that population on Twitter. Subsequently, examples of social networks produced by racially-charged cyber-aggressive tweets are graphically visualized to analyze their contents and determine the extent to which aggression spreads throughout the networks. Finally, a better understanding of how and when Twitter users may push back against or resist racially-aggressive messages is examined.

#### **DATA & METHODS**

#### NodeXL

To conduct this mixed-methods study I used an open-source social media importing software called NodeXL (Smith, et al., 2010). NodeXL allows users to import, collect, save, and analyze publicly available data (i.e. messages posted by public accounts and any relevant information associated with those accounts) that is released by notable social media companies such as Facebook, YouTube, Flickr, and Twitter. For this particular study, I used only the function that imports publicly released data from Twitter.

## The Sample & Data Collection

Over the course of the study, I conducted various 'term searches' on NodeXL using four racially-charged derogatory terms or phrases commonly associated with African-Americans. The search terms were as follows: search term 1 was 'co\*n,' search term 2 was 'porch monkey,' search term 3 was 'ni\*\*er,' and search term 4 was 'stupid ni\*\*er.' Collection of the data involved use of an importing function in the software and manually submitting the four racially-charged search terms. From there, NodeXL compiled the most recent number of tweets that were posted by public accounts containing the four search terms within seven to eight days prior to the search. Once a search was complete, NodeXL not only provided the textual content of the tweets themselves, but also the usernames of the accounts posting the tweets, the usernames of the accounts at which the tweets were directed (if the sender 'mentioned' another user with their username), whether the tweets were reposted by another user ('retweeting'), any hashtags that

might have been included in the tweets, and the URLs that linked directly to the posts themselves on Twitter's interface.

Several searches on NodeXL were conducted using the four terms over the course of two and a half weeks in January and February of 2018. Of those searches, four datasets – one for each search term – were downloaded. The number of tweets that were downloaded from these four datasets totaled 6,437. Of those, a sample of 800 tweets was analyzed in detail and interpreted as the main sample of tweets in the study, with 200 tweets coming from each term considered.

## Accessibility & Content Analysis of Cyber-Aggression in Twitter Messages

Once all of the information from a search was imported and compiled into a NodeXL dataset, I timed how long it took to come across the first tweet I classified as aggressive. This allowed me to examine how readily accessible racist messaging on Twitter is to any user. Next, I conducted a content analysis to manually review the contents of each of the tweets to document how many could be classified as aggressive in nature. When I came across tweets that I determined to be racially-aggressive, I followed the link provided from the NodeXL dataset to the Twitter page on which the tweet was situated. From there, I was able to view the online conversation that may have preceded or followed the tweet that was selected from the NodeXL dataset. This allowed me to contextualize the originally-selected tweet and more accurately determine whether it was used in a racially-aggressive manner.

#### **Analyzing Resistance to Cyber-Aggression**

Additionally, when possible and present, I analyzed and documented the accessibility and patterns of resistance that emanated from aggressive conversations or messages. In other words, I interpreted how frequently within the sample users lashed out in response to racial-charged aggression, attempted to rally support for themselves or another victim from the broader Twitter population, responded to aggression in a positive fashion, or called attention to a racist interaction they or someone else had encountered. The purpose of this was to gain a better understanding of how people respond to or resist racially-aggressive behavior on Twitter.

Additionally, I also documented numerous cases in which tweets posted by users were removed from Twitter for violating the company's media policy, as well as instances in which accounts were suspended for the same reason. When these situations occurred, it was a result of a tweet being so racially-aggressive that the site determined to remove the content and/or the account.

#### **Content Analysis of Negative African-American Stereotypes**

Next, I conducted a content analysis of each of the aggressive tweets I documented in the original NodeXL datasets. The content analysis was used to determine whether the racially-charged messages aligned with traditional anti-African-American stereotypes. The stereotypes I considered in this analysis were those that describe African-Americans as lazy, unintelligent, violent, and/or dependent. Additionally, I took note of which and how many aggressive tweets were unable to be classified by one of these stereotypical themes, as well as which tweets did not

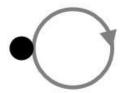
have enough context to determine any such theme. This last group of tweets was classified as 'indeterminable/other.'

## Network Analysis of Social Networks Containing Aggressive Twitter Messaging

I also conducted a network analysis of each of the searches made. Using a function on NodeXL, I was able to digitally 'visualize' any tweets and conversations that contained a particular racially-aggressive term to determine the extent to which the aggressive messages were able to spread within social networks. This network visualization function produced an illustration that displayed how various tweets containing the racially-aggressive terms were connected to each other and the ways in which they were being spread by users (i.e. if they were being 'retweeted', responded to, ignored, etc.). Each point, or node, in a visualization represents a tweet containing the designated aggressive search term or phrase. The lines, or edges, connecting all of the nodes show how certain tweets are connected to each other within Twitter conversations, as well as how often those aggressive tweets are being repeated throughout social networks. An edge that connects from one node to another with an arrow signifies that a person has either 'mentioned' another user or has 'retweeted' a post made by that user (see Figure 1). A node that is not connected to any others, but instead produces a circular edge that only connects to itself signifies that a user has posted a tweet but not mentioned any others (see Figure 2). In large network visualizations, each distinct Twitter conversation is signified by nodes of a specific color and shape. For example, in Figure 3 (an example visualization), all solid purple circular nodes belong to a specific Twitter conversation, while all hollow red square nodes are a separate conversation, and so on. Each tweet within the visualization contains the specific search term.



Figure 1. Example of Edge - Mention/Retweet



**Figure 2. Example of Edge - No Mention of Other User(s)** 

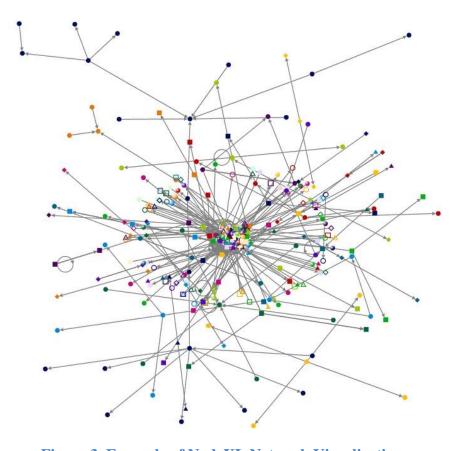


Figure 3. Example of NodeXL Network Visualization

#### **Limitations & Strengths**

There were limitations to this study, however. First and foremost, the data from this sample is only a tiny fraction of that which is made available to the public by Twitter, and an even smaller percentage of all the data that exists in the Twitter atmosphere as a whole. Considering the fact that over 500 million tweets are posted daily (Kirkorian, 2013), the sample may not adequately highlight the scale of aggression – or resistance to it – that is realistically appearing on the social media platform. Furthermore, interpretations of what terms and phrases constituted racially-charged cyber-aggression are subjective in nature. It is also important to note that while this study investigates cyber-aggression targeting African-Americans on Twitter, it is not meant to suggest that other demographic groups are not subject to similar online harassment. Twitter 'bots' also presented a challenge. In recent years, bots - automated accounts created to automatically post tweets without oversight by a human user - have become prevalent on Twitter. It was necessary that tweets produced by bots were not considered, meaning the challenge of determining what was posted by a human versus a bot became a tedious task to confront. However, it became evident that bots routinely posted messages that were essentially impossible to understand, using nonsensical grammar in their tweets. These types of 'bot' messages were excluded from this study.

Conversely, however, this study is one of the very first of its kind in that it explores the concept and nature of cyber-aggression in a manner that has seldom been investigated to this point. While previous literature has focused on the frequency with which individuals - namely adolescent youth within smaller educational and social networks - face aggressive behavior online (as well as the demographic characteristics predicting victimization and offending), little research has analyzed the nature of aggression in the broader and more anonymous online

atmosphere of Twitter. One of the potential contributions of this study is that it establishes a foundation upon which future researchers can build their investigations to more efficiently and accurately collect data regarding the nature, severity, and accessibility of aggression on social networking sites.

#### **RESULTS**

#### **Accessibility of Racist Tweets**

To determine how accessible aggressive tweets targeting African-Americans are on Twitter, I examined a sample of the 200 most recent tweets from each of the four datasets in the study. To do this, I recorded how quickly it took to come across a tweet that I considered racially-aggressive, that is, one using a derogatory term or phrase that typically targets African-Americans. Between the four search terms, it took an average of 22 seconds to identify a racially-aggressive tweet. Interestingly, there was some variability in the amount of time it took to identify an aggressive tweet based upon which term was being searched. For search terms 1 and 3 (co\*n, ni\*\*er), it took 55 seconds and 30 seconds, respectively, to identify the first aggressive tweet in the sample data. However, for both search terms 2 and 4 (porch monkey, stupid ni\*\*er) the first aggressive tweet was identified immediately. In these instances, the time recorded was listed as 1 second. It should be noted that the disparity in these timed results may have depended upon the time of day of the NodeXL search. More generally, however, it took less than 1 minute to find an aggressive message from any of the four racist terms.

There was also great variation in the frequency of each search term that was downloaded in the four datasets. Approximately 6,437 tweets containing one of the four search terms were downloaded between the datasets. Nearly 47% (3,014) of those tweets contained search term 1 (co\*n). About 38% (2,446) included search term 2 (porch monkey), roughly 8% (532) included search term 4 (stupid ni\*\*er), and the remaining roughly 7% (445) contained search term 3 (ni\*\*er). Note that search terms 1 and 3 are each only one word in length, as opposed to terms 2 and 4 which are both two words, which likely limited the sample size of the latter terms.

It also should be noted that these tweets were not all aggressive in nature. Many of contained the negative search terms somewhere within the body of the tweet, but the overall sentiment of the message was determined to be non-aggressive in nature. Keeping this in mind, the number of tweets classified as racially-aggressive were recorded by each search term.

Between the four search terms, just over 32% (259) of the downloaded tweets were determined to be racially-charged, with African-Americans, either as individuals or as a group, being the target of that cyber-aggression. Just over 33% (86) of those aggressive tweets resulted from search term 1, nearly 12% (31) were downloaded and classified using search term 2, while search terms 3 and 4 made up 28% (72) and 27% (70) of the aggressive tweets, respectively.

Another phenomenon that I encountered and subsequently recorded was the frequency with which sampled tweets and/or Twitter accounts were suspended as a result of violating Twitter's media and content policy. Of the sample of 800 tweets, just over 8% (67) of them were so racially-aggressive that the platform chose to remove that content and/or user from the site, which was likely a result of the tweet or account having been reported by another user. This data is displayed in Table 1.

**Table 1. Twitter Data Collected** 

Search Term	Total Tweets Analyzed/Downloaded	Aggressive Tweets	Resistance Tweets	Reported Tweets/Suspended Accounts	Time to Aggressive Tweets (in seconds)
Co*n	200/3,014	86 (33.20%)	6 (4.58%)	1 (1.49%)	55
Porch Monkey	200/445	72 (27.80%)	3 (2.30%)	55 (82.09%)	30
Ni**er	200/2,446	31 (11.97%)	58 (44.27%)	1 (1.49%)	1
Stupid Ni**er	200/532	70 (27.03%)	64 (48.85%)	10 (14.93%)	1
Totals	800/6,437	259 (32.34%)	131 (16.34%)	67 (8.34%)	N/A

## Themes in & Examples of Racist Twitter Messaging

Using a content analysis method, I also documented the underlying themes in racist

Twitter messages to determine whether they aligned with more traditional themes in anti-black
stereotypes. As was previously mentioned, there are longstanding societal perceptions of and
stereotypes against African-Americans in American society. These perceptions often hold that
African-Americans are lazy, unintelligent or ignorant, violent, and dependent upon others
(Devine and Elliot, 1995; Lapchick, 2000). After analyzing and interpreting those tweets that
were deemed racially-aggressive, it was determined that of the 259 tweets, approximately 19%
(49) conveyed an underlying message labeling the victim or target group as lazy. Approximately
4% (11) cast African-Americans as dependent upon others, while nearly 32% (82) promoted an
aggressive message casting the targets as unintelligent or ignorant. Rather surprisingly, only 2
tweets (.77%) targeted African-Americans as violent. The themes of approximately 44% (115) of
the tweets were classified as indeterminable or 'other,' that is, falling along the lines of a
different thematic message not considered. These findings are presented in Table 2, while Table
3 displays examples of racist tweets that follow each of the stereotypical themes considered.

**Table 2. Stereotypical Themes in Racist Twitter Messages** 

Anti-African-American Theme	Count (Percentage of Total)
Lazy	49 (18.92%)
Dependent	11 (4.25%)
Violent	2 (0.77%)
Unintelligent	82 (31.66%)
Indeterminable/Other	115 (44.40%)
Total	259

**Table 3. Examples of Stereotypical Themes in Racist Twitter Messages** 

Stereotypical Theme	Content of Tweet
Lazy	@USER1: "@USER2 @USER3 You tell them ni**ers to get off their lazy colored as*es"
Violent	@USER1: "Not sure if this is true but TBH lot of <b>blacks are violent sub human savages</b> . So I'm not gonna be mad about AG Sessions"
Unintelligent	@USER1: "Yeah Obama created more war, isis, didn't dig the U.S. out of recession, oh and in his first 2 years in office, Obama spent more money that Bush did in 8. Yeah thats something to be proud off, stupid ni**er didn't know how to count money."
Dependent	@USER1: "Not like they'll ever have a g***amn use for such a thing. F*ck all y'all stupid sorry porch monkey, government DI*K riding mother f**kers"

## **Network Visualizations & Examples of Racist Tweets**

Additionally, NodeXL contains a function that enabled me to digitally visualize the networks of tweets that emanated from the search terms used in this study. This portion of the study serves as a point of reference to better understand the extent to which racially-aggressive messaging can reach throughout Twitter. Below are the digital figures that were produced from the four datasets downloaded in this study. One point to note is that these figures display not just the sample of 200 tweets interpreted in each dataset, but the entire network of tweets from the overall search, that is, each of the 6,437 total tweets downloaded between the four separate data sets. It should be emphasized, however, that the several thousand tweets visualized in Figures 4-7 are only a tiny fraction of the total number of tweets that have been posted publicly that could be considered as racially-aggressive.

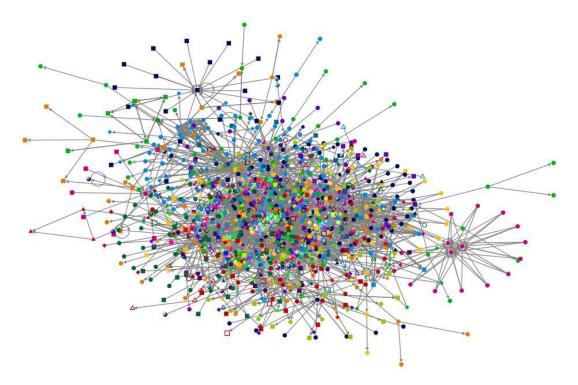
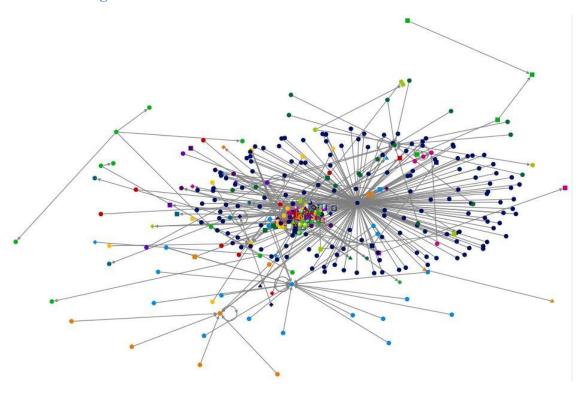


Figure 4. Search Term 1: Co\*n - Full Network Visualization



**Figure 5. Search Term 2: Porch Monkey - Full Network Visualization** 

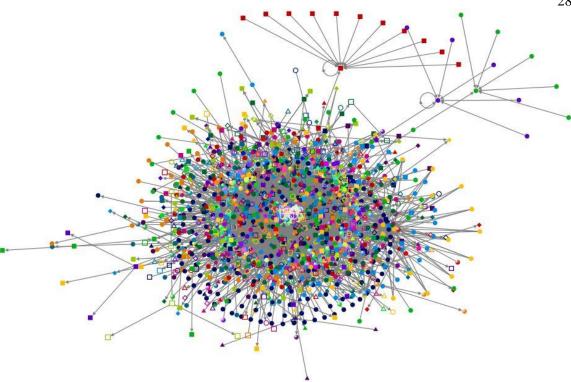


Figure 6. Search Term 3: Ni\*\*er - Full Network Visualization

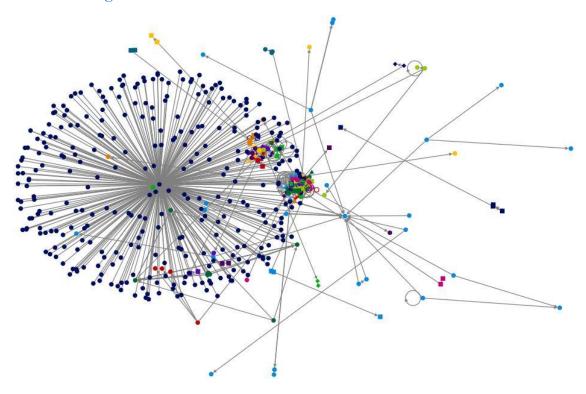


Figure 7. Search Term 4: Stupid Ni\*\*er - Full Network Visualization

Furthermore, I also examined conversations within these networks to document the actual content of racist tweets that was sent between users. Table 4 displays examples of the content of such messages, one from each search term. Figures 8-11 illustrate the network visualizations that emanate from each of the tweets in Table 4. The arrow next to each figure (8-11) signifies each of the example tweets from Table 4, from which the rest of the conversation network emanates. In these cases, the visualizations display the network spread of these racist messages. For example, in Figure 10 the tweet involves 76 people, many of whom retweeted that derogatory message.

**Table 4. Examples of Racist Tweets** 

Search Term	Content of Tweet	Accompanying Figure
Co*n	@USER1: "@USER2 Lying babbling fake fraud <b>co*n</b> fool. Video don't lie fraud"	Figure 8
Porch Monkey	@USER1: "@USER2 PLEASE GET OBUMHOLE AND THROW THAT SCAB <b>PORCH MONKEY</b> IN PRISON ."	Figure 9
Ni**er	@USER2: "@USER1 That @USER3 ni**er thought they were gonna win"	Figure 10
Stupid Ni**er	@USER1: "@USER@ @USER# @USER4 stfu u stupid ni**er you are so brainwashed like most libtards"	Figure 11

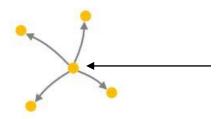
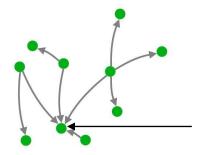


Figure 8. Example of Racist Conversation Network - Co\*n



**Figure 9. Example of Racist Conversation Network - Porch Monkey** 

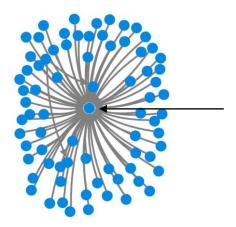


Figure 10. Example of Racist Conversation Network - Ni\*\*er

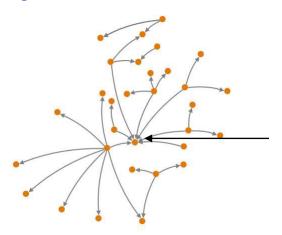


Figure 11. Example of Racist Conversation Network - Stupid Ni\*\*er

### **Reclaiming**

The concept of 'reclaiming' was an additional factor that was considered when interpreting the content of the examined tweets. As described by Tony Thorne, curator of the Slang and New Language archive at King's College London, 'reclaiming' of "ethnic and sexual slurs starts as an act of bravado by a few of the oppressed, then may become an empowering mechanism for a much wider community" and "replaces the discourses of power (Nunn, 2015)." In the context of this study, reclaiming was a concept employed by some Twitter users who appeared to be African-American and who sometimes chose to use terms that would otherwise be viewed as racially-aggressive. These terms were used to either describe themselves or people within their demographic group in an empowering manner.

In this study, instances of 'reclaiming' were documented by examining the content of the language surrounding the search terms. If users were also posting generally positive language or emoticons associated with or expressing positive emotions or followed the accounts of the other participants in the conversation, it was determined that they were 'reclaiming' this otherwise racially-aggressive language and likely did not intend to send a malicious message. Examples of actual tweets and the visual networks of such instances can be seen in Figures 12-13.



Figure 12. Example A of 'Reclaiming' Traditionally Racially-Aggressive Terms - Ni\*\*a



Figure 13. Example B of 'Reclaiming' Traditionally Racially-Aggressive Terms - Ni\*\*a

### **Intragroup Cyber-Aggression**

It should be noted, too, that not all of the tweets classified as aggressive were sent from individuals of a different racial group than their target(s). In some circumstances, aggressive tweets targeting African-Americans were also posted by users presumed to be of that same demographic. A small pocket of examined tweets of this genre produced interesting findings that warrant mention. In the dataset downloaded using search term 1 (co\*n), a considerable population of tweets targeted a prominent African-American public figure and were sent by users that seemed to be African-American as well. To provide context, this individual, Charlamagne Tha God (henceforth referred to as CTG), is a popular radio host. In one interview with prominent Afro-Latina hip-hop artist Amara La Negra, the topic of colorism and intersectionality was raised and CTG seemed to question the professional and social challenges faced by La Negra because of her mixed-race and gender. In response, many individuals on Twitter took to the social media site to attack CTG for his comments and question his motives. What follows is an example of the racially-aggressive tweets that targeted CTG.

@USER: "@cthagod You ah co\*n...#amaralanegra"

@USER: "Yeah, @cthagod goes in and out of Co\*n City."

@USER1: "@USER2 @USER3 Charlemagne is a co\*n. I don't like his as\*."

@USER: "@cthagod F\*\*king co\*n as\* ni\*\*a. Go back to taking white supremacists on dates you blight

on the black community."

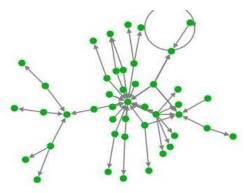


Figure 14. Example of Intragroup Cyber-Aggression - Co\*n

It should be noted that many of the users targeting CTG are using racially-aggressive language to attack him for his perceived insensitivity towards the issue of race and gender intersectionality. And, while the study was unable to definitively discern the race of the users targeting this public figure, given the context of the conversations, as well as profile pictures, these online aggressors appear to be African-Americans. Given that, this presents an interesting instance of African-Americans on Twitter using racially-derogatory language to target other individuals within their own demographic.

# Frequency in Victim Defense/Reporting of Aggression

I also recorded the number of tweets downloaded from each search term that were posted in resistance to an aggressor's harmful message. This was done as a means of trying to establish a stronger understanding of how Twitter users resist the frequent issue of racist messaging. Of the 800 total tweets examined, just over 16% of them (131) were posted by users either coming

to the defense of a victim targeted by racist aggression, defending themselves in such an instance, or calling attention to a racist interaction they encountered or witnessed themselves.

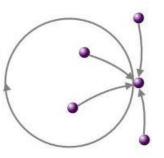
Nearly 49% (64) of the total number of resistance tweets included search term 4, while approximately 45% (58) included search term 2. Approximately 5% (6) and 2% (3) of these tweets were identified using search terms 1 and 3, respectively. An interesting point to note here is that these 'resistance tweets' were sometimes Twitter users defending victims or themselves from racist attacks, while also using racially-charged or overall aggressive language as a response. These results are also displayed in Table 1.

Examples of resistance to cyber-aggression can be seen in Figures 15-17. Figure 15 — gathered from search term 1 — illustrates a partial network of users retweeting an individual who "called out" another user's racist language in a conversation. Figure 16, from search term 4, is a partial network visualization of a user defending themselves after having been targeted for sharing an opinion of theirs, with other users retweeting her message. Figure 17, which includes search term 3, shows a larger network of users retweeting an individual for having called attention to a racist incident that they had witnessed, as well as the nodes created by people responding to the original tweet.



Figure 15. Example of Resistance to Cyber-Aggression - Co\*n, Ni\*\*er

Humor? How is that humor? How is someone calling you a "stupid nimer famot" humor? Please enlighten me because I damn sure don't know.



12:17 PM - 21 Jan 2018

Figure 16. Example of Resistance to Cyber-Aggression - Stupid Ni\*\*er

You call him a "nimer" but then run away? Smh.

9:14 AM - 18 Mar 2018

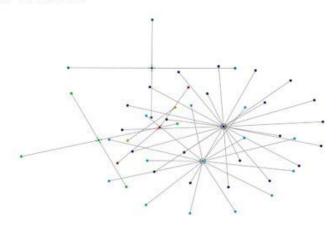


Figure 17. Example of Resistance to Cyber-Aggression - Ni\*\*er

#### **DISCUSSION & CONCULSION**

Overall, aggressive messages targeting African-Americans as individuals or a demographic are easily accessible to anyone with a Twitter account. This group faces frequent attacks and hostility online. It took an average of just over twenty seconds to encounter anti-African-American messages across datasets containing nearly 6,500 tweets. Considering that only four aggressive search terms were analyzed in this study and that there are countless other anti-African-American terms or phrases that could be used (e.g. jigaboo, monkey, ape, etc.), it could be presumed that even greater amounts of racially-charged messages likely exist in the vast expanse of Twitter. These findings align with the existing body of research into cyber-aggression and cyber-bullying that situates it as a widespread problem (Felmlee and Faris, 2016; Wang, Iannotti, and Nansel, 2009; Mishna et al., 2010; Mouttapa et al., 2004). In fact, this study found that roughly one-third (32.4%) of the sample was considered racially-aggressive, a result that closely mirrors the findings of Bartlett, Reffin, Rumball, and Williamson (2014), who concluded that as much as 30% of tweets posted daily that contain racial slurs are derogatory in content.

It was also found that there are common anti-African-American stereotypical themes employed by aggressors in Twitter interactions. Messages portraying African-Americans as unintelligent are particularly pervasive on Twitter (approximately one-third of the sample), while tweets insinuating that they are dependent are less common. The idea of African-Americans as violent was infrequent, but present. However, there were also additional stereotypical themes present in the datasets that were not considered in this study.

Moreover, aggressive slurs that have historically denigrating connotations are also present in online communications. Given the perceived anonymity afforded to Twitter users, it would not be unreasonable to consider the notion that racist aggression online is more pervasive

- or at least more overt - than in face-to-face interactions. There were frequent instances of racially-charged messages being posted by users whose accounts had no identifying features. That is, their accounts used animated profile pictures and cover photos, with no personal information, location, or anything that could be traced back to the individual perpetrating the attack, findings that align with those of Li (2007) and Wolak, Mitchell, and Finkelhor (2007). Given this, it is not much of a surprise that each of the search terms used produced extensive networks that digitally visualize how often these aggressive terms are posted, shared, and replied to on Twitter.

Racially-charged intragroup aggression is also a trend that, while not common, does occur within conversation networks given certain circumstances. Such interactions on Twitter were bred from situations in which users presumed to be African-American felt as though other individuals within their demographic group were 'turning their backs' on black culture and undermining the struggles of other minorities.

Furthermore, several instances of reclaiming were also uncovered in this investigation. In a specific circumstance, users called attention to the concept of intersectionality when an Afro-Latina woman's struggles were questioned. In this instance, those same users who defended the target and intersectionality also reclaimed racially-aggressive language to target the individual who initially victimized the woman in question. This case may serve as an example of the complex nature of racially-charged aggression on Twitter. While racist behavior is often perpetrated between different demographic groups as a means of establishing power structures (Sidanius, Devereux, and Pratto, 1992; Turner and Reynolds, 2003), given certain circumstances it also can be witnessed within groups.

Resistance to racist cyber-aggression, whether employed by the victim themselves or another Twitter user, also occurs in online conversations. While it was not found to be very common, it did happen within the sample with non-negligible frequency. However, defense of victims or resistance to aggressors often employed aggressive language as well, essentially creating a vicious cycle of victims, aggressors, and cyber-aggression, a trend also noted by Mouttapa et al. (2004).

While this study is one of the first of its kind, it should be noted that there are factors that should be considered in future research. Principally, Twitter only releases a small percentage of its publicly-available data to databases such as NodeXL. This factor alone limits the number of tweets that can be downloaded from the social media site to only a fraction of the hundreds of millions of posts that are made every day. Subsequently, the number of tweets that could be analyzed in this study was an even smaller portion of that total population. Taking that into consideration, this research was not intended to be a representative sample of the racially-charged aggression targeting African-Americans on Twitter as much as an introduction to its existence, prevalence, accessibility, and nature. In addition, given the nature of the content-analysis, subjectivity plays a role in the interpretations of results, and additional research is needed to document the generalizability of the results.

This study investigates an aspect of online behavior in a way that has rarely been examined to this point. Given the accessibility of cyber-aggression uncovered in this study, the prevalence of racist stereotypes, and the spread of aggressive networks, it is clear that cyber-aggression can entangle victims, aggressors, and other participants in vicious online conversations on a frequent basis. Cyber-aggression can be problematic for minority groups, as found here for African-Americans, and for other underrepresented racial groups as well

(Felmlee, Rhodis, and Francisco, 2018). The ease with which these messages can be accessed, as well as the themes that they often follow remains troublesome. However, that is not to say that these derogatory messages make up the only tweets exchanged in online communication. As exemplified by some of the examples of online messages described earlier, positive resistance to racist aggression is also present on Twitter, as well as instances of users simply calling attention to troubling, racist behavior. In tandem with research into aggressive online behavior and social awareness to the issue, social media companies should be encouraged to put forth concerted efforts to combat this relatively young yet persistent problem. In doing so, cyber-aggression may be mitigated to create healthier online environments. Given that much of our daily lives is increasingly shaped by the cyber world, this task remains a crucial one for our society.

#### **BIBLIOGRAPHY**

- Allan, H. T., Cowie, H., & Smith, P. A. M. (2009). Overseas nurses' experiences of discrimination: a case of racist bullying?. *Journal of nursing management*, 17(7), 898-906.
- Álvarez-García, D., Barreiro-Collazo, A., & Núñez, J. C. (2017). Cyberaggression among Adolescents: Prevalence and Gender Differences/Ciberagresión entre adolescentes: prevalencia y diferencias de género. *Comunicar*, 25(50), 89.
- Bailey, M. (2013). New Terms of Resistance: A Response to Zenzele Isoke. *Souls*, *15*(4), 341-343.
- Bartlett, J., Reffin, J., Rumball, N., & Williamson, S. (2014). Anti-social media. Demos, 1-51.
- Bauman, S., & Baldasare, A. (2015). Cyber aggression among college students: Demographic differences, predictors of distress, and the role of the university. *Journal of College Student Development*, 56(4), 317-330.
- Chatzakou, D., Kourtellis, N., Blackburn, J., De Cristofaro, E., Stringhini, G., & Vakali, A. (2017, June). Mean birds: Detecting aggression and bullying on twitter. In *Proceedings of the 2017 ACM on Web Science Conference* (pp. 13-22). ACM.
- DeSmet, A., Bastiaensens, S., Van Cleemput, K., Poels, K., Vandebosch, H., & De Bourdeaudhuij, I. (2012). Mobilizing bystanders of cyberbullying: an exploratory study into behavioural determinants of defending the victim. *Annual review of cybertherapy and telemedicine*, 10, 58-63.
- Devine, P. G., & Elliot, A. J. (1995). Are racial stereotypes really fading? The Princeton trilogy revisited. *Personality and social psychology bulletin*, 21(11), 1139-1150.

- Dovidio, J. F., Evans, N., & Tyler, R. B. (1986). Racial stereotypes: The contents of their cognitive representations. *Journal of Experimental Social Psychology*, 22(1), 22-37.
- Faris, R., & Felmlee, D. (2011). Status struggles: Network centrality and gender segregation in same-and cross-gender aggression. *American Sociological Review*, 76(1), 48-73.
- Faris, R., & Felmlee, D. (2014). Casualties of social combat: School networks of peer victimization and their consequences. *American Sociological Review*, 79(2), 228-257.
- Felmlee, D., & Faris, R. (2016). Toxic ties: networks of friendship, dating, and cyber victimization. *Social psychology quarterly*, 79(3), 243-262.
- Felmlee, D., Inara Rodis, P., Francisco, S. C. (Forthcoming). What a b!tch!: Cyber aggression towards women of color. In V. Demos & M. T. Segal (Eds.), *Advances in gender research: Gender and the Media*. Elsevier.
- Firebaugh, G., & Davis, K. E. (1988). Trends in antiblack prejudice, 1972-1984: Region and cohort effects. *American Journal of Sociology*, 94(2), 251-272.
- Gaertner, S. L., & McLaughlin, J. P. (1983). Racial stereotypes: Associations and ascriptions of positive and negative characteristics. *Social Psychology Quarterly*, 23-30.
- Haselager, G. J., Hartup, W. W., Lieshout, C. F., & Riksen-Walraven, J. M. A. (1998).Similarities between friends and nonfriends in middle childhood. *Child Development*, 69(4), 1198-1208.
- Hodges, E. V., Malone, M. J., & Perry, D. G. (1997). Individual risk and social risk as interacting determinants of victimization in the peer group. *Developmental psychology*, 33(6), 1032.
- Jussim, L., Coleman, L. M., & Lerch, L. (1987). The nature of stereotypes: A comparison and integration of three theories. *Journal of Personality and Social Psychology*, 52(3), 536.

- Katz, D., & Braly, K. W. (1935). Racial prejudice and racial stereotypes. *The Journal of Abnormal and Social Psychology*, 30(2), 175.
- Krikorian, R. (2013). New Tweets per second record, and how! [Web log post].

  Retrieved March 3, 2018, from <a href="https://blog.twitter.com/engineering/en\_us/a/2013/new-tweets-per-second-record-and-how.html">https://blog.twitter.com/engineering/en\_us/a/2013/new-tweets-per-second-record-and-how.html</a>
- Kowalski, R. M., Giumetti, G. W., Schroeder, A. N., & Lattanner, M. R. (2014). Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth.

  \*Psychological bulletin, 140(4), 1073.
- Lapchick, R. E. (2000). Crime and athletes: New racial stereotypes. *Society*, 37(3), 14-20.
- Li, Q. (2007). New bottle but old wine: A research of cyberbullying in schools. *Computers in human behavior*, 23(4), 1777-1791.
- McConahay, J. B., Hardee, B. B., & Batts, V. (1981). Has racism declined in America? It depends on who is asking and what is asked. *Journal of conflict resolution*, 25(4), 563-579.
- Menesini, E., Codecasa, E., Benelli, B., & Cowie, H. (2003). Enhancing children's responsibility to take action against bullying: Evaluation of a befriending intervention in Italian middle schools. *Aggressive Behavior*, 29(1), 1-14.
- Mishna, F., Cook, C., Gadalla, T., Daciuk, J., & Solomon, S. (2010). Cyber bullying behaviors among middle and high school students. *American Journal of Orthopsychiatry*, 80(3), 362-374.
- Mouttapa, M., Valente, T., Gallaher, P., Rohrbach, L. A., & Unger, J. B. (2004). Social network predictors of bullying and victimization. *Adolescence*, *39*(154), 315.
- Nansel, T. R., Craig, W., Overpeck, M. D., Saluja, G., & Ruan, W. J. (2004). Cross-national

- consistency in the relationship between bullying behaviors and psychosocial adjustment.

  Archives of pediatrics & adolescent medicine, 158(8), 730-736.
- Nunn, G. (2015, October 30). Power grab: reclaiming words can be such a bitch. Retrieved March 14, 2018, from https://www.theguardian.com/media/mind-your-language/2015/oct/30/power-grab-reclaiming-words-can-be-such-a-bitch
- Runions, K. C. (2013). Toward a conceptual model of motive and self-control in cyber-aggression: Rage, revenge, reward, and recreation. *Journal of youth and adolescence*, 42(5), 751-771.
- Sidanius, J., Devereux, E., & Pratto, F. (1992). A comparison of symbolic racism theory and social dominance theory as explanations for racial policy attitudes. *The Journal of Social Psychology*, *132*(3), 377-395.
- Sidanius, J., Pratto, F., Van Laar, C., & Levin, S. (2004). Social dominance theory: Its agenda and method. *Political Psychology*, 25(6), 845-880.
- Smith, M., Ceni A., Milic-Frayling, N., Shneiderman, B., Mendes Rodrigues, E., Leskovec, J., Dunne, C., (2010). NodeXL: a free and open network overview, discovery and exploration add-in for Excel 2007/2010/2013/2016, from the Social Media Research Foundation. Retrieved from https://www.smrfoundation.org
- Steeh, C., & Schuman, H. (1992). Young white adults: Did racial attitudes change in the 1980s?.

  \*American Journal of Sociology, 98(2), 340-367.
- Sterner, G., & Felmlee, D. (2017). The Social Networks of Cyberbullying on Twitter. *International Journal of Technoethics (IJT)*, 8(2), 1-15.
- Sue, D. W., Capodilupo, C. M., & Holder, A. (2008). Racial microaggressions in the life

- experience of Black Americans. *Professional Psychology: Research and Practice*, *39*(3), 329.
- Turner, J. C., & Reynolds, K. J. (2003). Why social dominance theory has been falsified. *British Journal of Social Psychology*, 42(2), 199-206.
- Wang, J., Iannotti, R. J., & Nansel, T. R. (2009). School bullying among adolescents in the United States: Physical, verbal, relational, and cyber. *Journal of Adolescent health*, 45(4), 368-375.
- Warman, D. M., & Cohen, R. (2000). Stability of aggressive behaviors and children's peer relationships. *Aggressive behavior*, 26(4), 277-290.
- Wegge, D., Vandebosch, H., Eggermont, S., & Walrave, M. (2015). The strong, the weak, and the unbalanced: The link between tie strength and cyberaggression on a social network site. *Social Science Computer Review*, *33*(3), 315-342.
- Wolak, J., Mitchell, K. J., & Finkelhor, D. (2007). Does online harassment constitute bullying?

  An exploration of online harassment by known peers and online-only contacts. *Journal of adolescent health*, 41(6), S51-S58.
- Wright, M. F., & Li, Y. (2013). The association between cyber victimization and subsequent cyber aggression: The moderating effect of peer rejection. *Journal of youth and adolescence*, 42(5), 662-674.

### ACADEMIC VITA

### **Academic Vita of Jordan Lawson**

jrlawson608@verizon.net

### **Education**

Schreyer Honors College, The Pennsylvania State University, University Park, PA

B.A. Sociology, B.A. Political Science

Honors in Sociology Graduation: May 2018

Thesis: "The Nature & Prevalence of Cyber-Aggression Targeting African-Americans on

Twitter"

Thesis Supervisor: Diane Felmlee

## Scholarships, Grants, & Fellowships Received

African/African-American Study (The Pennsylvania State University)

Barry Directorship Liberal Arts (The Pennsylvania State University, College of the Liberal Arts)

Schreyer International Study (The Pennsylvania State University, Schreyer Honors College)

Bunton-Waller Undergraduate Fellowship (The Pennsylvania State University)

Arnold & Bette Hoffman Professorship in Sociology (The Pennsylvania State University)

Pittsburgh Promise Scholarship (The Pittsburgh Promise)

### **Awards & Honors**

Paterno Fellows Scholar, 2014-2018 Schreyer Honors Scholar, 2016-2018

#### **Presentations**

Lawson, Jordan (2017). "Bigotry Takes to Twitter: Cyberaggression Towards African-Americans." Poster and research findings presented at the Undergraduate Research Exhibition at The Pennsylvania State University.

# **Community Service/Philanthropic Involvement**

2018

Head of Security

- -Assessed, updated, and implemented the entire security infrastructure for the world's largest student-run philanthropy event
- -Developed the security protocol for various events, each hosting between several thousand and tens of thousands of participants
- -Facilitated and oversaw the security education and training of 38 security captains and 1,000+ security committee members

Penn State IFC/PanHellenic Dance Marathon, University Park, PA

### **International Education**

International Studies Institute – Florence, Italy – 2017

## **Language Proficiency**

Proficient in Spanish

### **Work Experience**

August 2016-May 2018

Research Assistant

-Collected data on the nature and prevalence of cyber-aggression targeting minorities on Twitter, collaborated on comprehensive projects with faculty and research team Sociology and Criminology Department - Pennsylvania State University, University Park, PA Supervisor: Dr. Diane Felmlee

June 2017-August 2017

Business Development & Marketing Intern

- -Conducted research on companies targeting as potential clients and sought to develop preliminary business relationships
- -Facilitated the redevelopment of various outreach tools such as websites, capabilities statements, and preliminary contact letters
- -Produced and distributed necessary documents to procure contracts on construction projects such as bids, quotes, and proposals

6 Degrees Consulting, Inc., Pittsburgh, PA

Supervisor: Bob Lawson

June 2016-August 2016

Developmental Programs Staff Coordinator, Leaders-in-Training Program Coordinator

- -Developed and facilitated an in-service program for the entire staff, conducting interviews regarding staff members' personal and professional experiences, feedback pertaining to staff training and development programs, etc.
- -Created a report on staff responses and presented it to the administration, suggesting improvements to staff training and development program,
- -Created a curriculum for, revitalized, and facilitate a 2-week leadership development program for 15-year-old campers

Harry E. Sheldon Calvary Camp, Conneaut, OH

Supervisor: Samantha Borkavic

August 2015-December 2015

Dialogue Facilitator, Teaching Assistant

- -Facilitated candid dialogues focusing on contentious racial, gender, religious, political, and socioeconomic topics
- -Mediated small mixed-gender and -racial groups, built strong interpersonal relationships, and managed grades for 45 students

Sociology and Criminology Department - Pennsylvania State University, University Park, PA Supervisor: William Wise