THESIS

EXPLORING THE ROLE OF SOCIAL IDENTITY AND SOCIAL MEDIA IN UNDERSTANDING HUNTERS' PERCEPTIONS OF WILD PIGS AND THEIR MANAGEMENT IN THE U.S.

Submitted by

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ABSTRACT

EXPLORING THE ROLE OF SOCIAL IDENTITY AND SOCIAL MEDIA IN UNDERSTANDING HUNTERS' PERCEPTIONS OF WILD PIGS AND THEIR MANAGEMENT IN THE U.S.

This thesis presents two manuscripts that explored the role of social identity and social media in understanding hunter' perceptions of wild pigs in the U.S. Wild pigs (*Sus scrofa*), also known as feral swine, feral hogs, invasive wild pigs, or wild boar, are considered one of the top 100 most destructive invasive species in the world. They cause considerable damage to agricultural farms, native flora and fauna, property and cultural sites, costing the U.S. an estimated $1.5 billion a year in damages and control costs. There is a need for research to improve understanding of the social phenomena that exacerbate the problems associated with wild pigs, as well as provide insights to effective management policies. There is an inherent social dimension to the issue of wild pigs, due in part to their destructive nature that directly or indirectly impacts humans. In addition, human behavior can contribute to the cause as well as the solution to the wild pig issue. For example, research suggests that a driving force of wild pig population expansion is human-mediated translocation of these animals for the purpose of sport hunting. The control of wild pig populations is also tied to human behavior, given that it requires participation and cooperation among various stakeholder groups to reduce or limit the spread of these populations. Understanding the factors that inhibit or promote such behaviors is key to addressing this issue.

This master's thesis addresses this need in two unique ways: (i) the first paper engages with social identity to explore whether natural resource group affiliation may be a reliable

predictor of wild pig management preferences via a survey of Texas hunters; and (ii) the second paper develops a tool to aid in the analysis of large datasets generated by social media content focusing on sentiment and online representations of identity.

The first paper explored the role of social identity in relation to hunters' attitudes toward wild pig management strategies in Texas. Specific research objectives for this study were to examine: (1) Texas hunters' overall acceptability of different lethal and non-lethal management actions for wild pigs; and (2) whether that acceptability varied by hunters' affiliation with different groups, namely different categories of natural resource organizations (agriculture, hunting, conservation, and no affiliation). We assumed that if variation in levels of support indeed existed, our findings would provide a relatively convenient basis for managers to provide targeted information and outreach materials to the membership rolls of these organization. A total of 10 management methods were listed and analyzed. Of those 10, nine were considered lethal management methods – trap and kill, trap and sell, use of a toxicant, use of dogs, use of snares, lease hunting, owner/employee hunting, government or agency hunting, and aerial shooting. One method was considered non-lethal – the use of deterrents. The results shows that all management actions were completely acceptable by the majority of hunters except for the use of toxicants and the use of non-lethal deterrents. ANOVA results revealed that the mean acceptability score on each of the 10 management action items differed significantly across the four social identity categories but were relatively minor. Agricultural related groups were more accepting of lethal and non-lethal control methods for controlling wild pigs, while individuals who were not affiliated whatsoever with any identity group were much less accepting of these methods. Similar to other studies that have examined stakeholder group identification in relation to other wildlife species than wild pigs, our findings suggest that social identity-related factors

(i.e. group level influences) can influence acceptability of control methods for wild pigs, however effect sizes had a less than minimal or small effect.

The second paper explored Twitter, the most popular social media micro-blogging platform, to demonstrate how social media data can be leveraged to understand human-wildlife-related issues. In doing so, we developed a novel tool to mine twitter data to investigate sentiment and online identities relevant toward wild pig issues. The purpose of our study was to examine Twitter users' sentiment toward wild pigs vis-à-vis tweets, as well as the online identities involved. Specifically, online identities for the purpose of this study can be defined as social media users on Twitter, who self-report hobbies, sociodemographic characteristics, and occupations. It's extremely important to study online identity representation because of several reasons. First, individuals who use social media platforms may never be selected to do a survey specific to our study. Second, studying online identities captures a wider variety of attitudes than otherwise done so using traditional social science methods, like surveys. Specific objectives of this study were to: 1) determine which tweets were relevant or non-relevant and of those relevant tweets, 2) examine the overall sentiment associated with the dataset; 3) examine online identity via user profile description; and 4) determine the extent to which sentiment varied by online identity. To the best of our knowledge, an analysis of this kind has never before been conducted to automatically detect and identify sentiment toward wild pigs and online identity concurrently.

Our result indicated that the largest groups of online identity represented in our data were females and people whose occupation was in journalism and media communication. We found that users who identify with agriculture-related occupations had more favorable sentiment toward wild pigs. For the sentiment phase of analysis, the majority of our data indicated a negative sentiment toward wild pigs and other related search terms.

Overall, both chapters provided an important starting point for further investigation of the use of social media data and social identity in the context of natural resources related issues.

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DEDICATION

To my late father, Gregory, for showing me what a brilliant steward of the land resembles and instilling in me your passions and love for conservation, the outdoors, wildlife, and wild places. You should be here to celebrate this with me. For this, and a thousand other reasons, I dedicate this thesis to you.

This one's for you Pops. Love U.

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CHAPTER 1

SOCIAL IDENTITY AND ACCEPTABILITY OF WILDLIFE MANAGEMENT ACTIONS: A CASE STUDY OF WILD PIGS (*SUS SCROFA*) IN TEXAS

INTRODUCTION

Wild pigs epitomize a complex issue of critical importance to wildlife management. Wild pigs (*Sus scrofa*), also known as feral swine, feral hogs, invasive wild pigs, or wild boar (Keiter et al., 2016), are considered one of the top 100 most destructive invasive species in the world (Lowe, et al., 2000). First introduced by Spanish explorers in the 16th century, wild pigs have established in 35 U.S. states with an estimated population size of at least 6 million individuals residing on the landscape. Due to high reproductive rates and the ability to adapt to new areas easily, it takes only a few individuals to establish new populations (Bevins et al., 2014). They also have been recognized as contributors to the transmission of parasites, viruses, and bacteria, which pose severe risk to humans, domestic livestock, and other wildlife (Brown et al., 2019). Diseases of concern include Trichinella, Hepatitis E, Pseudorabies, Brucellosis, and Influenza A (Bevins et al., 2014). Moreover, wild pigs cause considerable damage to agricultural farms, native flora and fauna, property, and cultural sites (Anderson et al., 2016; McKee et al., 2020; USDA-APHIS, 2016), costing the U.S. an estimated $1.5 billion a year in damages and control costs (Elsey et al., 2012; Pimental, 2007).

There is an inherent social dimension to the issue of wild pigs, due in part to their destructive nature that directly or indirectly impacts humans. In addition, human behavior can contribute to the cause as well as the solution to the wild pig issue. For example, research suggests that a driving force of wild pig population expansion is human-mediated translocation

of these animals for the purpose of sport hunting (Grady et al., 2019; Hernández et al., 2018). The control of wild pig populations is also tied to human behavior, given that it requires participation and cooperation among various stakeholder groups to reduce or limit the spread of these populations. Understanding the factors that inhibit or promote such behaviors is key to addressing this issue.

Wildlife agencies have developed a variety of lethal and non-lethal methods to control wild pig populations and their associated impacts. Lethal methods (e.g., sharpshooting, toxicants) include tactics that typically aim to reduce the pig population size, while non-lethal methods (e.g., contraception, deterrents, and public education) are intended to result in less direct harm to the animals (Liordos et al., 2017). Management of wild pigs is a highly controversial matter that often creates conflicts among stakeholders and wildlife agencies, essentially creating a barrier to effectively addressing the problem (Colvin et al., 2015; Daniels & Walker, 2001). Wildlife managers are thus faced with increased challenges to develop control techniques that are both ecologically sound and cost-effective, while being socially acceptable to various publics (Heneghan & Morse, 2019).

Human perceptions of wildlife are frequently at the core of these social conflicts, as they can influence and determine how people respond to wildlife management (Manfredo et al., 2016). While a significant amount of literature exists on public acceptability of management actions for "native" species, including, for example, gray wolves (*Canis lupus*), black bears (*Ursus americanus*), coyotes (*Canis latrans*), and white-tailed deer (*Odocoileus virginianus*) (Heneghan & Morse, 2019; Sponarski et al., 2015; Urbanek et al., 2012; Vaske et al., 2013), little attention has been devoted to acceptability of control methods for "non-native" or "invasive" species, especially in the U.S. (Koichi et al., 2013). Further, much of the prior social science

research on wildlife-related issues has focused on individual attitudes, while neglecting to capture broader (e.g., group-level) perceptions and influences that can be a powerful driver of people's response to management actions (van Eeden et al., 2019). Some research has shown, for example, that an individual's identification with a group can affect how they perceive the acceptability of wildlife management techniques (Heeren et al., 2017; Lute & Gore, 2014; Naughton-Treves et al., 2003).

Given the important role of human perceptions and behaviors in affecting the abundance and distribution of wild pigs, as well as the success of long-term solutions to their management, social science can make a valuable contribution in this area (Baruch-Mordo et al., 2009). By understanding the conditions that make management strategies for non-native species such as wild pigs more or less acceptable to the public, managers will be better equipped to predict if conflict over the use of a given strategy is likely to occur. To contribute to this understanding and address important gaps in the literature outlined above, we applied social identity theory to examine the impact of group-level factors on the acceptability of wild pig management actions. More specifically, a social identity approach was used to understand hunters' attitudes toward management of wild pigs.

Social Identity

The social identity approach combines both social identity theory (Tajfel, 1978) and self-categorization theory (Turner et al., 1987). This combination of theories offers a useful framework that has been applied to understand conflicts in inter-group settings (Abrams & Hoog, 1990; Hornsey, 2008; van Eeden et al., 2019). Social identity is defined as "that part of the individual's self-concept which derives from their knowledge of their membership of a social

group (or groups) together with the value and emotional significance of that membership" (Tajfel 1981, p. 255). Self-categorization can be explained as:

> *People self-categorize as belonging to different groups (e.g., gender, political affiliation, and ethnicity) and how they identify with these categorizations is both shaped by their personal values and attitudes and, in turn, shapes their attitudes, behaviors, beliefs, etc. as they seek to align with what they consider members of that group should do or think* (Lute & Gore, 2014, p. 5).

According to this approach, individuals assign themselves to groups to protect and reinforce their own self-identity. Group membership can boost individuals' self-esteem by providing social meaning and decreasing doubt about appropriate behavior, attitudes, and norms. This approach can also be used to explain how groups form different values, beliefs, and attitudes (van Eeden et al., 2020).

Within a group, stereotypes are created about the 'ideal' group member. These stereotypes provide standards and guidance for how individuals should behave, essentially driving the group members to become role models and act in accordance with group norms (Hornsey, 2008; Tajfel et al., 1979; van Eeden et al., 2019). Individuals who do not conform to a group's values, attitudes, and norms belong to out-groups (Lute & Gore, 2014).

Empirical studies grounded in social identity theory suggest that individuals who affiliate with a particular group often have the same, or substantially similar, attitudes and preferences regarding an object or action of common interest. In the wildlife context, previous studies have found that attitudes toward management actions vary based on social identity or group affiliation (Hornsey, 2008; Tajfel, 2010; van Eeden et al., 2019). For example, van Eeden et al. (2019) used a social identity approach to understand variation in perceptions of lethal and non-lethal control

techniques among animal rights activists, wildlife conservationists, and farmers in Australia for four animals (kangaroos, wild horses, dingoes, and red foxes). Another study conducted by Koichi et al. (2013) examined the acceptability of methods used to control wild pigs in Australia among local residents and tourists, demonstrating that acceptability can be group- and context-specific.

With that, the unique contribution that this study provides focuses on inter-group social identity of hunter's and their preferences for wild pig management methods in Texas.

Research Objectives

As a case study application, we drew upon this theory and prior research to explore the role of social identity in relation to hunters' attitudes toward wild pig management strategies in Texas. Hunters play a unique role in both the control and range expansion of wild pigs in the U.S. and are therefore an important stakeholder group to understand. Despite the decreasing number of hunters in the U.S. (Decker et al., 2017), they continue to exert a significant influence on wildlife policy (Waldron et al., 2013). The influence of Texas hunters was apparent when the Texas Agriculture Commissioner approved limited use of a wild pig toxicant in February 2017. Less than a day after the Commissioner's announcement, the Texas Hog Hunters Association started an online petition opposing the toxicant, and within a week, the petition had garnered almost 2,500 signatures. They opposed the toxicant because they believed it to be unsafe, causing harm to humans, wildlife, and the ecosystem as a whole. Hunting groups also joined forces with environmental, meat processing, and animal welfare groups to lobby the Texas Legislature on this issue. On April 10, 2017, the Texas House of Representatives passed a bill requiring further study of any wild pig toxicant. Studying hunter's perceptions in Texas can provide insights on socially acceptable management strategies to avoid future conflicts.

Texas is an important state in which to explore the social aspects of wild pig management for several reasons. First, Texas has one of the largest populations of wild pigs in the U.S., with an estimated 2.5 million wild pigs in the state as of 2013 (Lewis et al., 2019). Second, a study conducted in 2014 showed that $190 million worth of crop production was lost due to wild pig damage, with Texas as the highest monetary loss to agricultural crops from an estimated eleven states with healthy wild pig populations (Anderson et al., 2016). Distribution maps provided in Figure 1.0 show the expansion of wild pigs in the U.S. from 1982 to 2019. The 2019 map illustrates how pervasive the wild pig population is on the landscape, showing that only one out of 254 counties in Texas is unoccupied by wild pigs (Figure 1.0).

Specific research objectives for this study were to examine: (1) Texas hunters' overall acceptability of different lethal and non-lethal management actions for wild pigs; and (2) whether that acceptability varied by hunters' affiliation with different groups, namely different categories of natural resource organizations (agriculture, hunting, and conservation). We assumed that if variation in levels of support indeed existed, our findings would provide a relatively convenient basis for managers to provide targeted information and outreach materials to the membership rolls of these organizations. For example, this research can inform development of communication strategies for promoting effective management responses to the wild pig issue, particularly for hunters. This specific research provides a unique contribution to both the applied and theoretical understandings of human dimensions of wildlife literature. First, we applied social identity to a new context (i.e. hunters and wild pigs in the U.S.). Second, group-level influences have not been readily explored and applied to issues surrounding wild pigs and their management in the U.S.

METHODS

Sampling and Data Collection

Data for this study were collected through a self-reported questionnaire administered through the online survey platform Qualtrics (Provo, Utah) (see Appendix A for full questionnaire). The sample for the study was provided by Texas Parks and Wildlife and consisted of every in-state and out-of-state Texas hunting license holder for the 2018-2019 hunting year who had an email address on record with the agency (n = 169,619). There is no wild-pig-specific hunting license issued in Texas, but during the 2018-2019 hunting year, any individual wishing to hunt wild pigs in Texas was required to hold a general in-state or out-of-state hunting license. All individuals in the sample were contacted by email, including one initial contact and two reminders, during the study period of June 4, 2019 to July 9th, 2019 and provided a link to the questionnaire on Qualtrics. The study was reviewed and approved for use with human subjects by the Texas A&M Institutional Review Board (IRB) (Protocol#: IRB2018-1219M; Reference # 083112).

Measurement of Key Concepts

Acceptability of Management Actions

Attitudes, which are defined as an evaluation of an object (e.g., favorable or unfavorable), which in this case would be each management action item (Fishbein & Ajzen, 2010). The evaluation of management actions are either as acceptable or unacceptable (Heneghan & Morse, 2019). It is important to understand management actions in terms of attitudes, because they provide information that may predict behaviors (Manfredo et al., 2004). The level of acceptability of various wild pig management actions was measured by asking respondents on a

five-point Likert scale (completely unacceptable [1] to completely acceptable [5]) to indicate whether different types of wild pig control methods are, or would be, personally acceptable. A total of 10 management methods were listed. Of those 10, nine were considered lethal management methods – trap and kill, trap and sell, use of a toxicant, use of dogs, use of snares, lease hunting, owner/employee hunting, government or agency hunting, and aerial shooting. One method was considered non-lethal – the use of deterrents. See Table 1.0 for an explanation of each method included on the survey.

Social Identity

To explore salient identities relevant to wild pig management in Texas, we treated affiliation with certain organizations as a proxy for an individual's social identity. The survey asked respondents to select which hunting, conservation or agricultural interest groups they were members of, out of 29 potential options (yes or no), including "none". Example groups included Texas Farm Bureau, Texas Pork Producers, Quail Forever, The Nature Conservancy, Ducks Unlimited, and Audubon Society (for a full list of groups, see question 7 in section 8 of Appendix A). Additionally, respondents were given a write-in option to list any other groups of which they were a member. The three categories (agriculture, hunting, and conservation) were determined based off of the types of identities that are most salient to wild pig management. Of the groups included on the survey, we assigned them to a specific category based on their main purpose/objective presented in their mission statement. For example, The Nature Conservancy's mission statement "is to conserve the lands and waters on which all life depends", making this specific group assigned to the conservation category.

Data Analysis

Survey data were analyzed using SPSS v.26 (Chicago, Illinois). A reliability analysis was conducted to examine internal consistency of the 10 acceptability items. This resulted in a Cronbach's alpha of 0.75, indicating sufficient measurement reliability (Vaske, 2008).

To address our research objectives we conducted descriptive analyses (e.g., frequencies) to explore the overall acceptability of management actions (objective 1); and one-way analysis of variance (ANOVA) with Tamhane's (used due to violation of equal variances assumption) post-hoc tests to explore differences in acceptability of management actions across social identity groups. Social identity variables were collapsed into four new dummy variables: (i) affiliation with only agriculture groups, (ii) affiliation with only hunting groups, (iii) affiliation with only conservation groups, and (iv) affiliation with no groups. Respondents who indicated they identified with more than one of the three categories (hunting, agriculture, conservation) were dropped from further analysis. Individuals who affiliated with more than one of the groups were not included in the analysis because we wanted to look at distinct differences in the three groups most salient to wild pig issues, rather than the combination of groups. Criteria for inclusion were $n > 100$ responses to indicate membership in each group, including the fill-in-the-blank 'other' category included on the survey. For the resulting groups, 'agriculture only' included a total of five groups: Texas Farm Bureau, Texas South Western Cattle Raisers, Texas Sheet and Goat Raisers Association, Texas Pecan Growers, and Texas Cotton Association. The 'hunting only' category consisted of 13 groups: Quail Forever, Ducks Unlimited, Texas Trophy Hunters Association, Pheasants Forever, Texas Deer Association, Houston Safari Club, Backcountry Hunters and Anglers, Rocky Mountain Elk Foundation, Safari Club International, Texas Hog Hunters Association, National Turkey Federation, Texas Dove Hunters Association, and Dallas

Safari Club. Last, seven groups were included in the 'conservation only' category: Exotic Wildlife Association, Audubon Society, Texas Master Naturalist, The Nature Conservancy, Texas Land Conservancy, Texas Forestry Association, and Coastal Conservation Association. Responses for the 'other' category provided over 100 new groups. However, to make the data more manageable, we chose to focus on respondents' first-mentioned group when they specified more than one, assuming that this group was likely most salient to them. From these responses, Backcountry Hunters and Anglers, Safari Club International, Rocky Mountain Elk Foundation, and Coastal Conservation Association met our criterion of $n > 100$ and were therefore included in the final analysis.

We used an alpha level of $p < 0.05$ to indicate statistical significance for all analyses. Effect size measures (eta) were calculated as an indicator of practical significance, due to the increased chance of finding statistical significance with large sample sizes. To determine acceptable effect sizes, criteria specified in the literature were used to denote minimal, typical, and substantial effects (eta > 0.10, 0.24, 0.37, respectively) (Cohen, 1988, Vaske, 2008).

RESULTS

Of the 169,619 surveys administered, 10,199 were undelivered, and 37,317 were returned, resulting in a 23% overall response rate. Respondents were almost exclusively male (96%), with the most prominent age group being 56-65 years old (26%). A bachelor's degree was the most common level of education (38%), and the most common average household income was $100,000 per year (65%). Of the respondents who remained in the analysis (61% of the total respondents, $n = 22,612$) following our classification procedures described above, approximately one in four identified with 'hunting only' groups (26%, $n = 5,824$); one in five

identified with 'agricultural only' groups (20%, *n* = 4,508); one in fourteen identified with 'conservation only' groups (7%, *n* = 1,671); and one in two identified with 'none' of the groups (47%, *n* = 10,609).

Objective 1: Acceptability of Management Actions

Overall, all management actions were considered completely acceptable by the majority of hunters in our study except for the use of toxicants and non-lethal deterrents. For example, descriptive statistical analysis (Table 1.1) indicated that 3.2% of respondents believed it to be completely unacceptable to 'trap and lethally remove' wild pigs, while 71.2% believed it to be completely acceptable. Additionally, 'aerial shooting' was completely unacceptable to only 6.6% of respondents, while 60.6% found it to be completely acceptable. 'Use of a toxicant' was believed to be completely unacceptable by 26.8%, while 31.7% of respondents believed this action to be completely acceptable, and 17.8% believed to be neutral regarding this type of action. Figure 1.1 shows all management actions by percentages.

Objective 2: Social Identity and Acceptability of Management Actions

ANOVA results revealed that the mean acceptability score on each of the 10 management action items differed significantly across the four social identity categories (Table 1.2). The acceptability of trapping and killing wild pigs differed significantly among social identity categories ($F = 28.17$, $p < 0.001$, eta = 0.004). Respondents in the hunting category showed the highest level of acceptability (m = 4.59), while the agricultural category had a lower mean acceptability of this action (m = 4.52). Individuals in the conservation category (m = 4.58) were not statistically different from these other two categories. Individuals who were not affiliated with any group showed significantly less acceptance of trapping and killing wild pigs (m = 4.45).

For the trap and sell method, only the hunting and none categories differed significantly, with mean acceptability scores of 4.23 and 4.16, respectively ($p = 0.001$).

Acceptability of using a safe and humane toxicant varied significantly across all groups, except agricultural and none, with means for hunting and conservation of 3.44 and 3.18, respectively ($p < 0.001$). For the use of dogs, agricultural differed from all other groups, with a mean of 3.97, ($p = < 0.001$). For the use of snares, agricultural differed significantly from none, with mean acceptability scores of 3.63 and 3.49, respectively. In addition, the hunting category differed significantly from the conservation and none categories for use of snares, with means of 3.66, 3.54, and 3.49, respectively ($p < 0.001$).

Lease hunting varied significantly between agricultural and hunting, with mean acceptability scores of 4.55 and 4.21, respectively ($p < 0.001$). For the owner and employee hunting methods, agricultural varied significantly from hunting and 'none' categories, with mean acceptability scores of 4.68, 4.62, and 4.63, respectively ($p < 0.001$). The hunting category significantly differed from all other groups on acceptance of government hunting, with a mean of 3.44 ($p < 0.001$). Lastly, acceptability of aerial hunting differed significantly among agricultural, hunting , and none categories, with means of 4.33, 4.27, and 4.11, respectively ($p < 0.001$).

For the one non-lethal method examined, deterrents, agricultural differed significantly from hunting, with means of 3.18 and 3.07, respectively. Additionally, hunting differed significantly from all other categories on this action, with a mean acceptability score of 3.07 ($p < 0.001$).

Effect sizes for these comparisons (eta = 0.001 to 0.015) indicated a less than minimal or small effect (Cohen, 1988; Vaske et al., 2008).

In summary, comparisons across the four identity groups showed that individuals who identified with a hunting group were more accepting of the use of toxicants than individuals affiliated with the other categories of groups we examined (mean = 3.44). Additionally, individuals who identified with an agricultural group were more likely to be accepting of the use of dogs (mean = 3.97), lease hunting (mean = 4.55), and aerial shooting (mean = 4.33) to control wild pigs than individuals from the other categories. Individuals who belonged to a conservation group were more accepting of the use of trap and sell methods (mean= 4.24), non-lethal deterrents (mean = 3.20), and owner/employee hunting (mean = 4.70) than members of other identity groups. Finally, of those individuals who did not affiliate with any group, the only method found more acceptable compared to other groups was government or agency hunting (mean = 3.68).

DISCUSSION

The primary objectives of this study were to examine the overall acceptability of management actions for wild pigs among Texas hunters and whether acceptability of such actions varied among hunters who affiliated with different categories of natural resource organizations – i.e., agriculture, conservation, and hunting. While other studies have shown that hunters, as a group, tend to be more accepting of lethal control methods for human-wildlife conflict scenarios (Liordos et al., 2017), this study was seeking to determine whether there are different identity groups with distinct management preferences among hunters.

In general, all management actions were considered completely acceptable by the majority of hunters in our study except for the use of toxicants and non-lethal deterrents. Hunters who affiliated with agricultural groups were more accepting of the full suite of lethal and non-

lethal methods for controlling wild pigs, while individuals who were not affiliated with any identity group were much less accepting of these methods. As the focus of our study was Texas hunters, these results are not generalizable to the general population of Texas or any other state. Nevertheless, these findings provide useful information for resource managers, as hunters constitute an important stakeholder group when it comes to wildlife management. We see that hunters are less accepting towards the use of a toxicant from previous research and this study, they do, however, approve of other lethal methods like of trap and lethally remove, lease hunting, and owner/employee hunting. Anecdotally, this finding is contradictory to the perception's mangers have regarding what hunters think about wild pigs and their management. Additionally, these finding can inform development of communication strategies for promoting effective management responses to the wild pig issues, specifically for hunters. Finally, this study can serve in the efforts to alleviate social conflicts among hunters who may have differing views about what constitutes appropriate management actions. Overall, this knowledge towards which methods are acceptable to distinct natural resources-related social groups among hunters, could be useful information for wildlife management agencies to effectively implement management programs for invasive wild pigs.

Similar to other studies that have examined stakeholder group identification in relation to other wildlife species than wild pigs (Bruskotter et al., 2009), our findings suggest that social identity-related factors (i.e. group level influences) can influence acceptability of control methods for wild pigs. However, the differences we detected among the four group types were small, in which we hypothesized several reasons why. First, affiliation by hunters with different types of natural resource organizations may not be a strong indicator of distinct social identity groups with significantly different wild pig management preferences. Second, social

identity/group level influences may not matter in this specific wildlife management context. Accordingly, tailoring outreach materials on the basis of membership in these organizations may not be an effective strategy for natural resource managers – at least in the context of wild pig management.

Importantly, this research should not be read to suggest that distinct social identity groups do not exist within the larger group of Texas hunters, as we only considered several natural resource group affiliations. Other possible indicators of distinct social identity groups could include achievement-oriented hunters, affiliation orientated hunters, or appreciation orientated hunters (Decker and Connelly, 1989). For example, some of those specific groups could be subsistence versus recreational/sport hunters, leisure or labor hunters, pro-wildlife management hunters, nature enthusiast hunters, and culturally influenced hunters.

There are several areas in which this study has contributed to the literature in a unique way. Prior research has not readily addressed distinct inter-group social identities of hunters and their management preferences for wild pigs. More broadly, social identity-related factors are often not studied as heavily in human dimensions of wildlife-related literature as individual-level factors like attitudes. Another area in which this study provides a unique contribution includes how we operationalized social identity. Previous studies within natural resource-related fields have operationalized social identity on surveys by asking to what extent respondents identified with particular identities of interest on which included ‘not at all’, ‘somewhat’, and ‘strongly’ (van Eeden et al., 2020; van Eeden et al., 2019). Our study took a different approach by examining membership affiliations with different organizations that could be classified into distinct categories as a proxy for social identity. Twenty-nine dichotomous variables were included on the survey asking to select all of the wildlife, environmental, or agricultural interest

groups of which they were a member. An analytical grouping of each of these interest groups were created in an attempt to represent social identity of inter-group memberships. Our results suggest these groupings, although statistically significant, had minimal effect sizes. With that, the way in which we categorized the different group types could have made an influence on the statistical outcomes of this study.

Future research could benefit from focusing on several study limitations. First, there is a need to explore additional measures of social identity variables, such as questions on how to operationalize social identity. For example, other types of questions about group affiliation beyond 'yes' and 'no' are warranted (e.g., 'how strong do you identify with the norms of group X?'). Second, there is a need to study other social identities that are salient to wild pig management outside of natural resource-group affiliations. Such future considerations paired with findings of both current and prior research will improve the understanding of the group-level factors that influence acceptability of control methods for wild pig management and that will eventually define the success of wild pig management outcomes for wildlife agencies.

Table 1.0. Explanation of management actions used for controlling wild pig populations

Type of Management Action	Explanation of Management Action
Trap and lethally remove	The use of traps to capture and humanely euthanize
Trap and sell	The use of traps to capture, euthanize and sell
Safe, human toxicant	The use of a humane toxic bait to control wild pigs
Use of dogs	The use of hunting dogs to locate/detect wild pigs
Use of snares	The use of steel cable snares, either neck or leg, to capture wild pigs
Non-lethal deterrents	The use of fencing, repellants or mechanical devices to control wild pigs
Lease hunting	The use of hunting through leases to control wild pigs
Owner/employee hunting	The use of property owner/employee hunting to control wild pigs
Government or agency hunting	The use of government or agency hunting to control wild pigs
Aerial shooting	The use of a helicopter to aerially shoot wild pigs

Table 1.1. Descriptive percentages for the acceptability of management actions

Management Action [1]	Completely Unacceptable (%)	Somewhat Unacceptable (%)	Neutral (%)	Somewhat Acceptable (%)	Completely Acceptable (%)
Trap and lethally remove	3.2	2.7	7.6	15.3	71.2
Trap and sell	6.1	5.3	12.7	17.2	58.7
Safe, humane toxicant	26.8	12.6	17.8	11.1	31.7
Use of dogs	8.5	9.0	17.9	18.4	46.2
Use of snares	13.4	11.7	19.2	16.5	39.2
Non-lethal deterrents	21.8	10.6	27.2	10.8	29.7
Lease hunting	3.3	2.5	9.5	16.7	67.9
Owner/employee hunting	1.3	1.1	6.8	14.9	75.9
Government or agency hunting	15.8	7.9	18.0	15.0	43.2
Aerial shooting	6.6	4.8	11.3	16.7	60.6

[1] Management actions coded as (1) completely unacceptable, (2) somewhat unacceptable (3) neutral, (4) somewhat acceptable, and (5) completely acceptable.

Table 1.2. ANOVA results for comparing acceptability of management actions across social identity categories

Management Action [1]	Agricultural Only (n=5,824) (26%)	Hunting Only (n=4,508) (20%)	Conservation Only (n=1,671) (7%)	None (n=10,609) (47%)	*F*-value	*p*-value	Eta(η)
Trap and lethally remove	4.52[a]	4.59[b]	4.58[ab]	4.45[c]	28.172	<.001	.004
Trap and sell	4.20[a]	4.23[ab]	4.24[a]	4.16[ac]	5.248	.001	<.001
Safe, humane toxicant	3.03[a]	3.44[b]	3.18[c]	2.99[a]	87.524	<.001	.012
Use of dogs	3.97[a]	3.88[b]	3.87[bc]	3.79[cd]	23.893	<.001	.003
Use of snares	3.63[a]	3.66[ab]	3.54[ac]	3.49[c]	18.053	<.001	.003
Non-lethal deterrents	3.18[a]	3.07[b]	3.20[a]	3.16[a]	6.033	<.001	<.001
Lease hunting	4.55[a]	4.21[b]	4.43[c]	4.48[c]	109.846	<.001	.015
Owner/employee hunting	4.68[a]	4.62[b]	4.70[a]	4.63[b]	9.606	<.001	.001
Government or agency hunting	3.62[a]	3.44[b]	3.67[a]	3.68[a]	27.791	<.001	.004
Aerial shooting	4.33[a]	4.27[ab]	4.19[bc]	4.11[c]	45.011	<.001	.006

[1] Management actions coded as (1) completely unacceptable, (2) somewhat unacceptable (3) neutral, (4) somewhat acceptable, and (5) completely acceptable.

[2] Means with different superscripts across each row are significantly different at $p < .05$ using Tamhane's post-hoc tests.

[3] All values are statistically significant at $p < .001$.

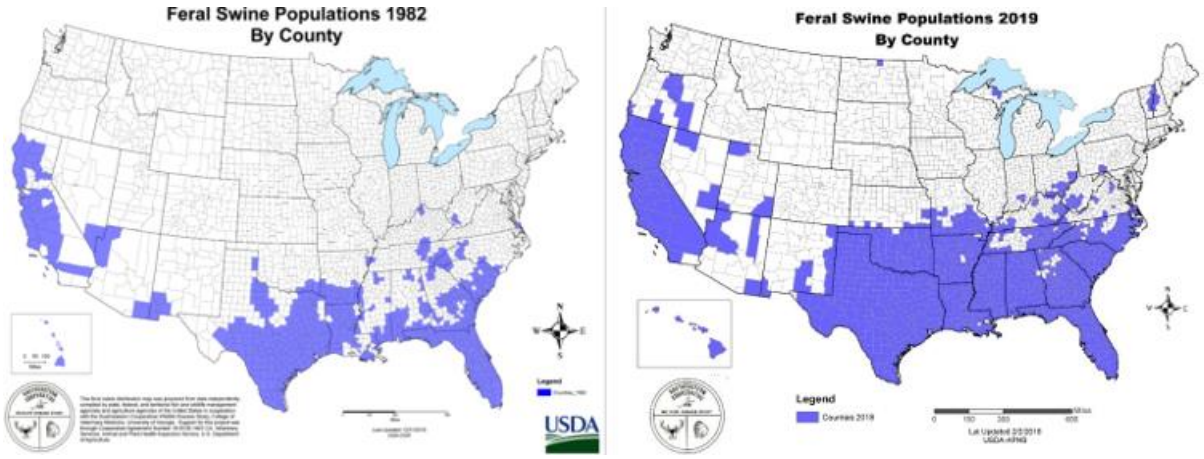

Figure 1.0: Wild pig populations by county in 1982 and 2019 (United States Department of Agriculture, "History of Feral Swine in the Americas", 2020).

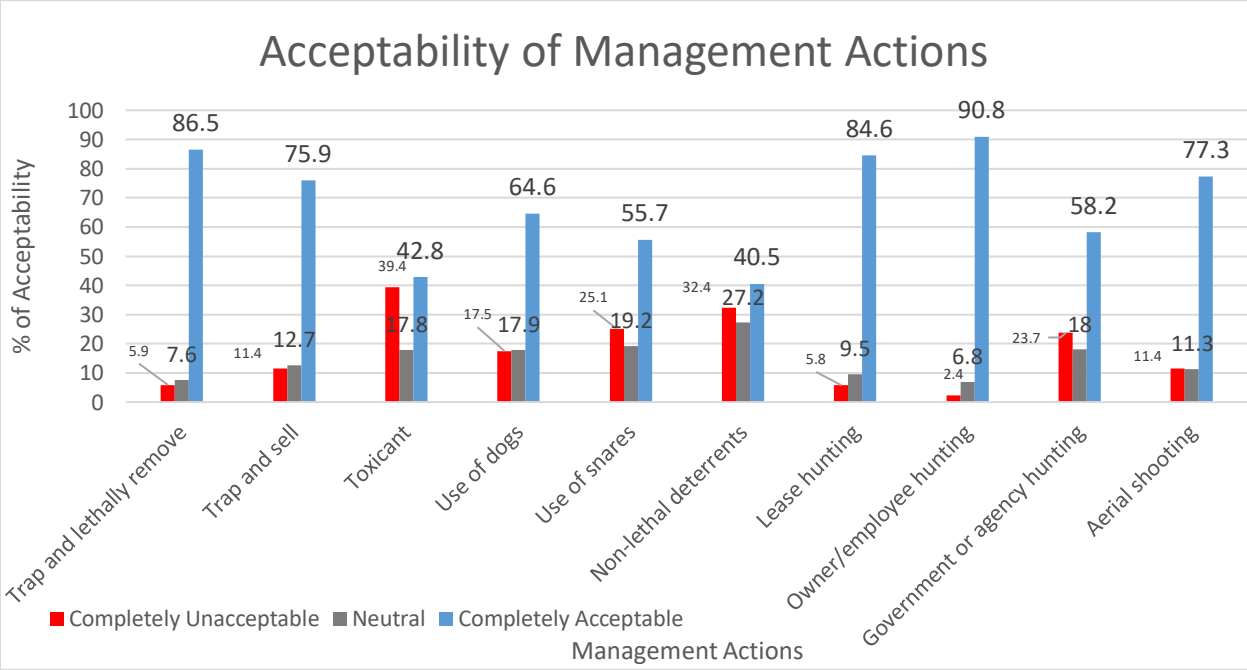

Figure 1.1 – Percent acceptability of wild pig management actions.[1]

[1] All management actions by percentages where 'somewhat unacceptable' was collapsed within the 'completely unacceptable' category. Similarly, 'somewhat acceptable' was collapsed within the 'completely acceptable' category, resulting in three new categories of either completely unacceptable, neutral, or completely acceptable.

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CHAPTER 2

TWITTER AS A TOOL FOR WILDLIFE-RELATED RESEARCH: THE CASE OF WILD PIGS

INTRODUCTION

For decades, surveys have been the most prevalent method to study human attitudes, perceptions and behaviors within the social sciences (Chew & Eysenbach, 2010; Sloan et al., 2015). Despite their popularity, surveys have a number of downsides for researchers. For example, they can be costly to implement, design, and analyze, as well as create real-time lags in data acquisition, which may limit their usage. Additionally, surveys have several biases associated with them, one of which is self-selection bias. Self-selection bias suggests there are some individuals who are more likely to participate in a survey than others, leading to a systematic bias. Systematic bias occurs when there is a sampling error produced from how the research is piloted.

To aid in addressing the challenges and limitations associated with surveys and other traditional social science methods (e.g., interviews), "big data" – i.e., data gathered from 'a vast range of transactional and naturally occurring sources' (Sloan et al., 2015, p. 2), is increasingly being exploited by researchers to investigate an extensive range of social phenomena. One commonly used source of big data were social media-generated content. Social media has proven to be a powerful source in disseminating and communicating information of societal importance (Crooks et al., 2013). Social scientists are now taking advantage of this trove of rich data, made possible through technological innovations, to evaluate and understand patterns of human-environment interactions and concerns (Song et al., 2020).

Twitter, the most popular social media micro-blogging platform, has an estimated 330 million monthly active users worldwide and generates billions of messages daily, making this social networking site an exceptional tool for studying diverse sets of people and their opinions (Daume, 2016; Kabakus & Simsek, 2019; Tamburrini et al., 2015). Twitter allows users to post short messages, known as "tweets," which can be up to 280 characters in length (Sansone et al., 2019). On average, 473,000 tweets are sent every minute, and 46% of Twitter users tweet daily (Madden et al., 2013). The result is an enormous quantity of rich data that holds great statistical power on the opinions of internet users with broad coverage across space and time (Reyes-Menendez et al., 2018; Tamburrini et al., 2015). Twitter data has been evaluated on an array of different natural resource-related topics, ranging from conservation science (Bombaci et al., 2016) to environmental and public health (Palomino et al., 2016), and natural disasters (Woo et al., 2015). Examples include Chew and Eysenbach's (2010) research on use of the terms 'H1N1' versus 'swine flu' over time, and Palomino et al.'s (2016) analysis of both tweets and hashtags to further understand the sentiment surrounding nature-deficit disorder.

Twitter data were analyzed more frequently than other forms of social media data because of its wide accessibility. This is due in part to Twitter's more generous data availability to the general public. For example, Facebook has extremely strict privacy settings on messages and overall, less users (Philander & Zhong, 2016). Also, Twitter's high value for research can be attributed to its open networking structure, which allows users to follow anyone without seeking approval from the receiving party.

> *The interactions among Twitter users can be viewed as a large network of sensors that react to external and social events, thus making it particularly suitable for studying the public opinions of these events* (Philander & Zhong, 2016, p. 17).

Twitter does, however, have certain disadvantages that may make it an inappropriate source for some studies. Considered the most 'data light' of the social media platforms, Twitter data lacks basic demographic information on users, creating a considerable gap for researchers. As a result, it is often regarded as a less reliable source of big data to study (Sloan et al., 2015). This skepticism for big data use – which is not limited to Twitter – may partially explain the paucity of innovative applications or tools that leverage big data in the context of natural resource-related research (Daume, 2016), including research concerning human-wildlife interactions. With that, some argue it is incumbent upon social science researchers, more generally, to respond to the arrival of new data sources and examine how they can apprise us of the social world. To be clear, the argument is not that social media data were a replacement or a proxy for data collected through traditional methods, but rather that social media data can supplement other forms of data collection to enhance our understanding of social phenomena. This ultimately raises practical and theoretical questions concerning whether and how big data can be integrated into natural resource-related research. Such questions are of increasing urgency given the seriousness of today's conservation and environmental challenges (Rahman, 2020). Given the stakes, big data content deserves both methodological exploration and assessment (Daume, 2016).

Study Purpose and Objectives

To demonstrate how social media data can be leveraged to explore human-wildlife-related research questions, we developed a novel tool to mine twitter data to investigate sentiment towards wild pigs, an invasive species in the U.S. with significant social, ecological, and economic impacts. Wild pigs (*Sus scrofa),* also known as feral swine or wild hogs, cause enormous damage to agriculture (Anderson et al., 2016; Mckee et al., 2020); negatively impact

ecosystems through their rooting (i.e., foraging) and wallowing behaviors; and pose a risk of disease transmission to humans, livestock, and companion animals through the transmission of pathogens (Brown et al., 2019).

Introduced by Spanish explorers in the 16th century, wild pig populations began increasing dramatically in size and distribution in the 1990's and are now established in an estimated 35 U.S. states with up to 6.9 million individuals (Boyce et al., 2020; Goedbloed et al., 2013; Lewis et al., 2019; Mayer & Brisbin, 2008). Their high intelligence, paired alongside a generalist diet and the ability to acclimate to a wide range of regions, has contributed to the widespread growth and establishment of wild pig populations (Bevins et al., 2014). Early maturation before the age of one and high fecundity rates in sows result in up to two litters per year, with as many as six piglets per litter (Higginbotham, 2013). This combination of early sexual maturity, opportunistic eating, and well-established populations is making it arduous for managers to control wild pig densities and the resulting damage. Further, anthropogenic influences have contributed to the vast expansion of wild pig populations (Grady et al., 2019). For example, previous research suggests that the expansion of wild pigs is attributed to human-mediated movement, or transport to new areas for the purpose of sport hunting. Grady et al. (2019) found, for example, that wild pig populations expanded to almost 70 counties in the state of Tennessee through hunter-mediated translocation. Given the important role of human thought and behavior in influencing the abundance and distribution of invasive species such as wild pigs, as well as long-term solutions to their management, social science is needed to better understand the human dimensions of this situation.

The purpose of our study was to examine Twitter users' sentiment toward wild pigs vis-à-vis tweets, as well as the online identities involved. Specifically, online identities for the purpose

of this study can be defined as social media users on Twitter, who self-report hobbies, sociodemographic characteristics, and occupations. It's extremely important to study online identity representation because of several reasons. First, individuals on social media platforms may never be selected to do a survey specific to our study, inevitably allowing us to study a wide array of individuals that we would have otherwise lost. Second, studying online identities captures a wider variety of attitudes than otherwise done so using traditional social science methods, like surveys. Specific objectives were to: 1) determine which tweets were relevant or non-relevant and of those relevant tweets, 2) examine the overall sentiment associated with the dataset; 3) examine online identity via user profile description; and 4) determine the extent to which sentiment varied by online identity. With that, this study provides a unique contribution to the wild pig issue both practically and theoretically. By determining the research objectives listed, managers can be better equipped to tailor and develop online communication strategies for effective wild pig management specific to the online identities represented in this study. Theoretically, this study captures online identities and sentiment via a machine learning approach that, to the best of our knowledge, has never before been conducted.

METHODS

Data Collection

The data collected targeted specific messages ("Tweets") posted to the micro-blogging service, Twitter. The messages are accessible through two public Application Program Interfaces (APIs): streaming API and public API. An API is a computing interface to a program (Twitter) that makes a connection with servers to retrieve specific information. The information retrieved is based on a pre-defined set of conditions, or filters relating to the objects of interest. For this

study, we used the search API, which retrieved Tweets that matched a set of predefined keywords. The keywords that were chosen for this study included the terms “wild pigs”, “wild hogs”, and “feral swine”. We used these different terms due to the lack of consistency in how scientists, wildlife managers, and the general public refer to the species (Keiter et al., 2016). All three keyword phrases had the potential to capture a broad array of users’ opinions about wild pigs, as well as the online identities involved. Tweets selected for analysis met two criteria for inclusion. Identified tweets had to be (i) written in English, and (ii) relevant to the wild pigs/hogs/swine theme. Geolocation was not a criterion for inclusion, as geotagged tweets account for only about 1% of all messages sent via Twitter (Longley, Adnan, & Lansley, 2015). We evaluated tweets over the time period from the 1st May to 4th November 2019. This timeframe was long enough to ensure that we captured a large and diverse sample of tweets, but not so long that it yielded an unwieldy number of tweets for purposes of training and evaluating the algorithms. Rich metadata fields downloaded from the API included not only the Tweet text, but also geo-location, timestamp, user profile description, username, user followers, user friend count, and retweet information (Table 2.0).

Python, a high-level programming software, was used to scrape tweets specific to the keywords identified earlier and to analyze our data. To address our research objectives, we used a two-step process. First, we manually labeled a sample dataset of tweets with a pre-determined coding scheme for relevancy, sentiment, and online identities. Next, we used a machine learning approach to classify and infer our entire dataset for all three topics that were manually labeled. We began with manually labeling a small, sample dataset, and then applied it to the entire, larger dataset.

Measurement of Key Concepts and Coding Schemes

Relevance

Twitter users post tweets for a wide array of reasons, and, given that, not all tweets would be directly relevant to our research objectives. Thus, we measured relevancy of tweets as being closely connected or appropriate to wild pigs. We used a binary (0,1) manual classification scheme to code a sample of tweets. Many tweets were considered and coded as relevant. However, some tweets were considered irrelevant during our coding process. Examples of the non-relevant topics found throughout the manual coding stage included the movie "Wild Hogs", the television show "Peppa Pig", and motorcycle (sometimes referred to as "hogs") or guinea pig references. If the tweet was not fully comprehensible due to a lack of context or complete sentences, it was also considered irrelevant. Tweets with URL links and no other content were also excluded (e.g., '*Wild pigs https://t.co/cEi0pyEqVC').* Thus, determining relevancy prior to applying classification algorithms to the dataset was a necessary exercise prior to determining sentiment and online identity.

Sentiment

Sentiment mirrors underlying emotions, which can be largely classified as positive, neutral, or negative (Becken et al., 2017). Sentiment analysis and opinion mining are forms of data analysis methods used to evaluate attitude expression within text (Fink et al., 2020). For example, a positive sentiment tweet appears as, "yes, that's the malay name for bearded pigs. they are known to be gardeners of the forests; they reshape soil to help organic matter decomposition. these wild pigs provided meat for humans living in guaniah over the last 40,000 years." In contrast to a positive tweet, a negative tweet would read, for example, "A prime example is wild hogs. They impact habitats about the same as if you ran heavy equipment over

it. They just decimate ground nesting birds and animals. They dirty water with mud and feces, and they're REALLY REALLY mean."

> *Scoring sentiment is an analytical approach that converts subjective and unconstructed text into constructed data. The purpose is to extract information that reveals critical events and assists in determining the emotional tone behind textual data in order to gain an understanding of opinions* (Becken et al., 2017, p. 90).

Analysis of this kind comes with challenges such as streamlining complex text so that a clear, overriding context can be recognized and inferring meaning from grammatical mistakes with ease (Becken et al., 2017). Although these challenges may be cumbersome, sentiment analyses have been used broadly across various disciplines to examine topics such as policy information, public health issues, disease outbreaks, and to communicate the importance of conservation science to professionals (Bombaci et al., 2016; Chew & Eysenbach, 2010; Culnan et al., 2010; Merchant et al., 2011; Paul & Dredze, 2011).

Tweets for this study were analyzed as an opinion toward the object of interest, wild pigs. We chose sentiment toward wild pigs because we wanted to understand the emotional tone behind the tweet in order gain a full comprehension of internet opinions. We used polarity of -1, 0, and 1 for negative, neutral, and positive sentiment, respectively, for the coding scheme. For examples of relevancy and sentiment of manually coded tweets, see Table 2.1**.**

Online Identity

To measure online identity, we used the rich metadata field known as user description, which is also known as 'feed identity' in some literature (Walton & Rice, 2013). User descriptions are considered online identity expressions for this paper (Prinate et al., 2016). Online identities are defined as hobbies/interests, occupations, or sociodemographic

characteristics. Here, individuals can fill in a description about themselves, usually making statements about attitudes or beliefs, hobbies, and sometimes information relating to employment (Sloan et al., 2015). A codebook (Appendix B) was created to include 'broader codes', 'finer codes' and 'explanations' for each identity. Identity categories were chosen after thorough examination of a subset of user description profiles during the relevancy and sentiment analyses phases to ensure all identities were being captured within the identity analysis phase. For this study, there were eight overarching 'broader' identities including occupational identity, gender and sexual orientation identity, spousal and parental identity, religious identity, political identity, ethnicity identity, interest/hobby identity, and membership/government identity. Explanations of these broader identities are as follows:

(1) Occupational identity: self-described based on career, profession, or occupations. An example of this expression is "*Female dairy farmer (4th generation), assistant to veterinarian, lawyer by day dedicated to defending family farms of the NY Foodshed*".

(2) Gender & Sexual Orientation identity: self-described based on gender and sexual orientation. Examples of this expression are *"cadejo/Jane. Korps PR. might be a raccoon, stay tuned! Bi/Pan/NB/trans/28/She/Her"* and "*Working on wildlife health issues #plastic #contaminants #parasites #pathogens. @LiberEroFellows @environmentca. She/her. Mom. Settler. Tweets are mine".*

(3) Spousal & Parental identity: self-described based on spousal and parental relationships. This category includes grandparent identities. An example of this expression is *"Father, husband, gamer, YouTube (he/him)"*.

(4) Religious identity: self-described based on membership in religious groups. An example of this expression is *"Midwest Buddhist libertarian socialist. Descendant of the colonized and the colonizer. Amateur religious scholar. they/them"*.

(5) Political identity: self-described based on political affiliation, parties/groups-relating to politics. An example of this expression is *"#MAGA Patriot!! Momma of 4!! I seek truth! Loud and proud Texan! Love POTUS!! #God Bless America"*.

(6) Ethnicity identity: self-described based on ethnic group-relation. An example of this expression is *"| Xavier | 22 | Black | Aspiring game designer | Hoping for a better world |"*

(7) Interest/Hobby identity: self-described based on activities, interests, or hobbies in which an individual participates or has an affinity. An example of this expression is *"Science, History, politics, social justice, & other stuff. Out & proud Aspie. Biotech student at @RIT, background in software. He/him pronouns"*.

(8) Membership/Governmental identity: self-described membership affiliation with a governmental agency, organization, or university. An example of this expression is "*Country, Family, NRA Life Member, Pro-life, MAGA, KAG, Support Our Vets, Build the Wall"*.

For each of the eight broader categories, another coding scheme was created to narrow down, in more detail, subcategories associated with each identity, known as 'finer codes.' The finer-coded categories included 18 occupations, 4 genders, 3 spousal-related, 5 parent/grandparent-related, 7 political affiliations, 8 religious' orientations, 7 sexual orientations, 6 ethnicities, 29 hobbies/interests, and 4 membership/governmental affiliations.

For some of the other categories, the Twitter user had to use the term within their user description to be considered in the analysis or use opposite or negative expression regarding a

category. For example, "*They can delete us.....but we always come back! We will not be silenced! I'm just here to support our President and fuk with liberals!"* would be considered in the Anti-Liberal/Pro-Conservative category. Lastly, if the individual placed emphasis on a hobby or interest, we made inferences on which category that individual will be placed. For example, *"Statistics, analytics, NFL game video analysis. Exposing fallacies. Facts trump opinion. (Header image taken from Hubble Space Telescope). Lover of wildlife"* is placed in hobbies categories that include 'sports' and 'animal lover/advocate' for the mention of the NFL and 'lover of wildlife' expressions.

The dataset in which the manual coding scheme was created was then applied to our Identity Classifier, mentioned in the *Identity Classification* section. A binary classification scheme (0 = no ,1 = yes) was created if an individual fell into any of the categories. In many cases, individuals fell into multiple identity categories, meaning these categories were not mutually exclusive of each other. Some identity categories were ultimately removed from analysis based upon small probabilities of being within a specific online identity category and directly irrelevant to wild pig related issues (i.e. 'pro-life' or 'feminism'). To aid in classification accuracy, some identities were bundled into a single category (Appendix C). For example, of the three 'finer' coded categories, 'Outdoorsman/woman', 'Angler', and 'Hunter', all were bundled into one identity called 'Outdoorsman/women'.

Relevance Classification

The objective of this process was to label all 48,557 tweets as either relevant or not. For this purpose, we used a machine learning approach in which we trained a classification algorithm on a smaller subset of manually labeled data and then used the trained algorithm to label all data. Our labeled training data consisted of 1,360 tweets that were randomly selected from each batch

of search results with probabilities weighted by the size of each batch so that we obtained a set of sample tweets that was representative of all the tweets we collected. The number of tweets that were labeled was limited by time constraints and informal examination of how classification accuracy was affected by the amount of training data. Of the tweets that were manually labeled, 70% were relevant.

After labeling our sample data, we investigated five simple algorithms (i.e., naïve bayes, support vector, logistic regression, standard multilayer perception, and random forest) based on a bag-of-words (BOW) approach. The BOW approach is used to extract certain features from text so that the text itself can be used in machine learning algorithms easily. The sentence structure of the text is discarded, while only focusing on whether or not a word occurs within the "bag" of the dataset of interest. Specifically, the BOW approach does not focus on where the word occurs within the dataset, just that it does exist. Therefore, to organize data for these algorithms, we combined all text from all tweets to form a single document, then removed punctuation, non-English words, and stop words (e.g. is, the, a), before converting all characters to lower case. We then retained the 1,000 most common words (tokens) that appeared in the document. To construct the set of features used by the algorithms, a column was created for each of the 1,000 words, and the row of each tweet received a one if the tweet contained the word, and a zero otherwise. Thus, our final dataset for these algorithms consisted of a column vector of labels (1 = relevant, 0 = non-relevant) with 1,360 elements and an array of features with 1,000 columns and 1,360 rows.

To evaluate algorithm performance, we relied on k-fold cross-validation with five folds and four different accuracy metrics (accuracy, precision, recall, f1). In the k-fold procedure, we split the data into five parts, trained on four of those parts, and validated on the remaining part.

The training process was repeated a total of five times such that each fold was used for validation exactly once. Accuracy metrics from each validation fold were retained and then averaged across the four validation folds to get an estimate of expected out-of-sample accuracy.

After evaluation of these simple algorithms, we proceeded to a more sophisticated approach to aid in the shortcomings of the BOW-based approaches and that used word embeddings and a convolutional neural network (CNN). Specifically, BOW does not account for word order, only partially accounts for context, and cannot exploit information about words that do not appear in the training data. Word embeddings refer to vectors that represent the meaning of a word. These are typically extracted from algorithms that have been trained on very large amounts of text. As a result, word embeddings are available for nearly every English word. The advantage of using word embeddings is that words that appear in similar context tend to have similar embedding vectors. Furthermore, words that only appear in validation or test data will have known embeddings, and if the algorithm has been exposed to similar vectors in training, it can extract relevant information - even from words it has not seen. Finally, by representing each tweet as a sequential vector of word embeddings, we could exploit word order and additional context information to determine relevancy.

We examined two different sources of word embeddings. One was Stanford's GloVe embeddings (https://nlp.stanford.edu/projects/glove/) that were trained specifically on tweets, and the other was Google's more general Word2Vec embeddings (https://code.google.com/archive/p/word2vec/). To organize the data for these embeddings, we again tokenized the text by removing punctuation, stop words, etc. The 1,000 most common words were retained, and each was assigned an integer. Each tweet was then converted to a sequence of integers. Since tweets vary in length, we pre-padded all sequences with zeros such

that all tweets had the same length sequence (63). The word embedding vector was then obtained for each integer and the word it represented. Each tweet was represented by a two-dimension array of numbers where each row represents a word, and each column is one of the elements of the embedding vector. As an example, Word2Vec embeddings are 300 elements long. Accounting for all 1,360 tweets and our maximum sequence length, our input data had 300 rows, 63 columns, and 1,360 sheets. Thus, our input data consisted of more the 25 million individual data points. This was challenging to analyze, especially when considering the need to allow for potentially complex interactions and non-linearity. This challenge is what motivated the use of a CNN. CNNs are a type of neural network that attempts to reduce the number of weights that need to be estimated (http://papers.nips.cc/paper/250-optimal-brain-damage.pdf). They are common in computer vision applications for this reason.

A full presentation of artificial neural networks (and CNNs, more specifically) is beyond the scope of this analysis, but a basic understanding is desirable. At the most basic level, neural networks can be viewed as very powerful function approximates. If a conventional neural network is reduced to its most simple form, it is equivalent to linear regression for a continuous output or logistic regression for a binary outcome (Figure 2.0). By adding layers of parameters (weights), the algorithm can account for more complex interactions and relationships. Parameters in each layer are estimated by through a sequential process of updating to minimize a specified loss function. The primary challenge with conventional neural networks is the extremely large number of weights that need to be estimated.

CNNs rely on a process of sliding windows (filters) over the input data to extract relevant features. Each filter contains a set of weights that are updated as the filter “slides” over the data (Figure 2.1). The size of the filter defines the amount of context information that is considered

when extracting relevant features. The architecture of the network is defined not only by the sizes of filters used, but also the number of each size, as well as the embedding layer and any dense layers included (Figure 2.2).

After exploration of different architectures and fine tuning other hyper parameters, the final step of the process was to re-train the network using all labeled data, and then use the trained algorithm to apply labels to all of the data.

Sentiment Evaluation

The process used for sentiment estimation was similar to what we used for relevance. We began by labeling the same 1,360 tweets with a measure of sentiment toward wild pigs that took the values -1, 0, or 1 for negative, neutral, and positive respectively. However, we only included relevant tweets (n = 926) in the remainder of the training process since we wanted to estimate sentiment toward wild pigs specifically. Of the labeled tweets, about 43% were labeled negative, 43% neutral, and 14% positive toward wild pigs. We then trained the same set of algorithms (except the GloVe-based CNN) and evaluated the accuracy of each using the same k-fold cross-validation procedure.

After selecting the best performing algorithm, we re-trained on all data and then labeled each of the 48,557 tweets. Although we predicted a discrete measure (-1, 0, 1) of sentiment for each tweet, we also calculated expected sentiment for each tweet as:

$$E[sentiment] = -1 * \widehat{\Pr}(-1) + 0 * \widehat{\Pr}(0) + 1 * \widehat{\Pr}(1) = -\widehat{\Pr}(-1) + \widehat{\Pr}(1)$$

where $\widehat{\Pr}(\cdot)$ are the class probabilities given by the classification algorithm. This is a valuable measure because it better accounts for conflicting language in the tweet and any ambiguity in our labeling process.

Identity Classification

This was a more challenging classification problem for several reasons. First, it relied on text in the user description field of the user's profile, and the amount of information in this field was often sparse. Second, rather than two or three identity categories, there were 33 different categories that we used to classify users. We again relied on the same sample of tweets we used for the relevance and sentiment analyses. Most rows had zeros, but some rows had multiple identities.

The multi-label nature of identity classification necessitated a modification to the output layer of our CNN. In the case of relevance, we used a single sigmoid activation function that output a single probability (of being relevant). In the sentiment CNN, we used a softmax activation function in the final layer to ensure the probabilities assigned to -1, 0, and 1 summed to one. In the identity problem, we had more than two classes, but we did not want to restrict the sum of probabilities to one since a user could belong to multiple identity categories. Because we essentially had 33 binary classification problems, we specified an output layer with 33 nodes, each with a sigmoid activation function. Our CNN architecture was further modified by using 750 epochs and specifying 64 filters of each size and 64 nodes in the dense layer. Architecture and hyper-parameter tuning relied on the same 5-fold cross-validation procedure used in the other two classification problems. After final tuning, the algorithm was retrained and applied to all collected tweets.

Sentiment by Identity Classification

Finally, we computed identity-specific sentiment by averaging the sentiment of each tweet weighted by the estimated probability that the user belonged to the identity. Thus, for a given identity, tweets from users that we are more confident belong to the identity get weighted more heavily. The first step was to remove non-relevant tweets, which left us with 36,739 tweets. We then computed the weighted mean sentiment for identity i according to

$$sentiment_i = \sum_{t=1}^{36,739} \widehat{Pr}(i)_t * E[sentiment_t] ,$$

which states that, when calculating the average sentiment of an identity, the sentiment of a given tweet is weighted by the probability that the author belonged to the identity in question.

RESULTS

Over the time period from the 1st May to 4th November 2019, a total of 48,557 tweets were collected and stored in a database. A breakdown of the number of total tweets not including relevancy by search terms are as follows: "feral swine" (n = 3,622), "wild hogs" (n = 25,274), and "wild pigs" (n =19,661). The highest count of tweets was generated during the week of 5th August 2019 (Figure 2.3). This was due in large part to the "30-50 feral hogs" meme that went viral on 4th August 2019. [2]

[2] A tweet emerged on August 4th, 2019 in response to Jason Isabell, a musician, about his opinion that "no one needs an assault weapon". The response tweet that went viral read "Legit question for rural Americans - How do I kill the 30-50 feral hogs that run into my yard within 3-5 mins while my small kids play?"

Relevance Classification Results

Our results indicated that the CNN based on Google's Word2Vec was the best performing algorithm (Figure 2.4) with an accuracy approaching 90%. It was the best performer in three of the accuracy metrics, including the two-general metrics. It was only outperformed by a random forest algorithm on recall, which means that the random forest algorithm labeled a higher percentage of the true relevant tweets as relevant. However, the random forest algorithm also had the second-lowest precision, indicating that the algorithm was labeling the majority of tweets as relevant without much discriminatory power. The final architecture of the CNN is presented in Figure 2.5.

The final result of this classification exercise was that 93% of rows from the feral swine search, 69% of rows from the wild pig search, and 75% of rows from the wild hog search were correctly labeled relevant. Thus, we substantially reduced the number of irrelevant tweets in our analysis through this exercise. Additionally, to ensure within coder reliability, the same dataset was manually coded twice: once on November 13, 2019 and again on December 16, 2019. The within coder reliability, Cronbach's Alpha was 0.993, providing excellent internal consistency.

Sentiment Estimation Results

The Word2Vec-based CNN was again the best performing algorithm with an accuracy of 72.5%. The architecture and optimization methods were unchanged from the relevance classifier with the exception of a slightly higher dropout rate (0.5 instead of 0.4). We also examined how incorrect predicted classes were distributed in the data (Figure 2.6).

Our classifier displayed the worst results on true positives. This was expected given the relatively small number of these examples in the training data. We also examined how expected

sentiment varied across the data (Figure 2.7). These results largely mirror those displayed in Figure 2.6, with expected sentiment for true positives displaying the most variability.

After labeling all 48,557 tweets, we plotted the distribution of sentiment across the original three search terms (Figure 2.8). The distributions for search terms “wild hog” and “wild pigs” are heavily skewed to the left, indicating more negative sentiment. The “feral swine” search term, though mostly negative, has a wider distribution of polarity.

Identity Classification Results

Two accuracy metrics were used: simple accuracy and exact match ratio (EMR). Because there were so many zeros (i.e., 1 = yes, 0 = no for an identity in question) in the labels, achieving high accuracy was straightforward. Our CNN achieved accuracy of about 98.5%. However, note that this only marginally improves on the accuracy of labeling all tweets zero. Thus, EMR is a better metric. In the case of EMR, a row is deemed correct if all classes are correctly predicted for that row. Our EMR was 67.6%. This relatively low EMR is less problematic than it may appear. We were not interested in discrete identity labels, but rather the probability that a user belongs to each identity.

The identities with the largest representation were ‘Female’ and ‘Journalism and Media Communication’. About 6% of users fell into each of these categories. Overall, the sample was quite unbalanced. Averaging across groups, about 1.7% of users fell into each group. For example, if 3% of users fall into identity A, 1% in B, we average all of those across which results in 1.7% average across groups. In general, it was unlikely from our sample for an individual to fall into one of the identity categories.

Sentiment by Identity Results

Table 2.3 shows the average sentiment for each identity category along with category size. Category size should be interpreted as an indication of sample size; it is the sum, across all users, of the probability of belonging to the identity. Sentiment toward wild pigs is measured on a -1 to 1 scale, -1 one being negative and 1 being positive. As shown, the most negative sentiment toward pigs (-0.78) includes Twitter users that affiliate with government organizations. On the opposite end, the least negative sentiment toward wild pigs (-0.57 and -0.61) are Twitter users that mention wild pigs as a part of their hobbies or interests, as well as users that included anti-environmental descriptions. However, the sizes of those identity categories are small, at 68.17 and 1.00, respectively. The second-least negative sentiment toward wild pigs is the Agriculture identity, which has a category size of 178.29. This means that individuals who identify with agriculture-related occupations, like farmer or rancher, view wild pigs relatively more favorably. The largest representation of identities on Twitter in our sample were Female, Male, Journalism and Media Communication Occupations, Parent, Spouse, and Academic Occupations.

DISCUSSION

We developed a unique tool that uses machine learning to extract relevant data from large datasets on the social media website Twitter. We then applied this tool to evaluate sentiment and online identities pertaining to a natural resource issue: invasive wild pigs. Of the extracted total tweets, 70% remained relevant after applying the machine learning algorithm. This step was of critical importance because it allowed a filtration process to occur, essentially weeding out all tweets that did not relate to our research objectives. Of the online identities examined with this

new tool, the sample was highly unbalanced, indicating that although the machine learning algorithm exhibited a fairly high degree of discriminatory power, there is still opportunity to fine-tune the classifier to detect a greater number of online identities on Twitter.

We found that Twitter is a rich source of data regarding internet users' sentiment toward wild pigs. In conducting a sentiment analysis, we found that the majority of the tweets in our dataset were more negative than positive. In particular, the distribution of sentiment for the search terms 'wild hog' and 'wild pigs' was heavily skewed towards a negative sentiment. The 'feral swine' search term, although negative, had a wider distribution of polarity, which may be explained by the identities of Twitter users who use the term. The term 'feral swine' is not commonly used by the majority of internet users, or the general public. Instead, the term was primarily used by academics and individuals from government agencies. This result suggests that there may be potential confusion about the words being used to describe wild pigs between the general public and the scientific community. With that, this result speaks heavily about the importance of terminology in communication and outreach efforts relating to wild pig management. The implications that may result because of this finding could aid in more effective communication and management for wildlife managers. We then computed identity-specific sentiment to estimate the probability that a Twitter user belongs to a particular identity. We found that the largest groups of online identity represented in our data were females and people whose occupation was in journalism and media communication. Interestingly, we found that users who identify with agriculture-related occupations had more favorable sentiment toward wild pigs. This is in contrast to previous research using traditional survey methods to understand farmers' and ranchers' attitudes towards wild pigs, which found that the majority of individuals

from those groups hold negative attitudes toward wild pigs in Texas (Adams et al., 2005). More research is needed to determine why such differences exist between studies.

Other studies have found that people engage in social media when they encounter or learn of an event that is outside of their daily norm (Cassa et al., 2013). This type of engagement was evident in our dataset with the "30-50 feral hog" meme that went viral during the sampling timeframe. The feral hog meme also contributed to a wide array of identities found on Twitter that may not have been detected otherwise.

Overall, there are limitations with social media research, as well as limitations that were specific to this study and could potentially be addressed in future research. English was one of our criteria of inclusion for analysis; however, future analysis of different languages could increase the robustness of findings while broadening the generality and diversity of the dataset. Furthermore, because one of our objectives was to study online identities, we chose to include as many identities that emerged from our dataset as possible. Because of the large number of identities that we classified and the relatively small number of individuals who fell into any given identity, it was more difficult for the classifier to predict the probability of a Twitter user falling into a particular classification. Future research that streamlines the number of identity groups by focusing on online identities most salient to the wild pig issue may therefore be warranted.

This research provides an important starting point for further investigation of the use of social media data in the context of natural resource-related issues. The model used could lend itself to investigating other social phenomena on Twitter (Savage et al., 2013; Sloan et al., 2015). Sloan et al. (2015), for example, recommends using the user description field to investigate archives of tweets to determine hobbies, and thus identify money spent on goods. In the context

of invasive species management, we could explore this avenue to determine money spent or economic losses inflicted by wild pigs on specific online identities. For example, researchers could evaluate how much money hunters are spending on gear to hunt wild pigs, or other wildlife species. With refinements to the model, another additional area where our tool could be used is focusing on areas where wild pig populations are being monitored for management purposes. Lastly, refining this tool should be done to identify themes in social media data. For example, a more refined tool could identify what users are tweeting about in regard to wild pigs (e.g., concern, damage, hunting, gear-used for hunts, etc.). An analysis of this kind has potential to generate new and useful information about the content being shared regarding wild pigs. As supplementary to this research, future research should consider ethnographic studies surrounding wild pig issues. This type of research has the potential to aid in identifying levels and perceptions of reality that might otherwise be missed when analyzing social media-related research. Thus, the methods presented in the paper, when applied, has made for a distinctly unique approach for social science research.

Table 2.0. Relevant meta-data stored in this project

Twitter given Variable Name	*Variable Label*
text	Tweet text
user_desc	User defined description
lang	Language of Tweet
created_at	Time tweet created
user_loc	User generated location
user_followers_count	Count of user followers
user_friends_count	Count of user friends
retweet_count	Count of retweets
user_name	Username

Table 2.1. Examples of coded tweets

Relevance

Relevant

- Sounders of wild hogs are the reason I carry a firearm while riding my bicycle early in the morning in Arizona. I've had them charge me, but fortunately, I've not had to shoot at one yet.
- The meme went viral, but wild pigs are a serious threat.
- Wild pigs causing 'ecological disaster' as they spread rapidly across Canada, survey says.

Irrelevant

- @NetflixFilm @netflix wild hogs
- Are there any wild guinea pigs or do they only live as pets?

Sentiment

Positive

- yes, that’s the malay name for bearded pigs. they are known to be gardeners of the forests; they reshape soil to help organic matter decomposition. these wild pigs provided meat for humans living in guaniah over the last 40,000 years.
- More project fear around the steady recovery of Europe’s iconic wildlife. Wild boar play a crucial role in the healthy functioning of European ecosystems. Referring to them as wild hogs´ or a feral pig is a way of delegitimizing their place here.

Neutral

- WILD HOGs fleeing from flood waters on overtopped levee in St Marys Parish, LA from hwy 317!!!
- I don't guess I know the difference. Feral hogs aren't the same as wild pigs?

Negative

- A prime example is wild hogs. They impact habitats about the same as if you ran heavy equipment over it. They just decimate ground nesting birds and animals. They dirty water with mud and feces, and they're REALLY REALLY mean.
- There are numerous ways to deal with the issue of wild hogs, and assault rifles aren´t one of them.

Table 2.2. Sentiment by Identity

Identity Category	Sentiment Average	Category Size
Academic Occupations	-0.74	499.99
Agriculture Occupations	-0.63	178.29
Animal Advocate Interests/Hobbies	-0.73	362.91
Anti-Environment Interests/Hobbies	-0.61	1.0
Armed Forces Occupations	-0.74	55.57
Asian	-0.77	11.44
Black/African American	-0.76	3.34
Business and Computers Occupations	-0.65	109.56
Conservative Ideology	-0.73	159.59
Criminal Justice, Political Science, and Legal Aid Occupations	-0.72	26.32
Female	-0.72	1735.71
Government Organizations	-0.78	0.24
Healthcare Occupations	-0.72	23.61
Journalism and Media Communication Occupations	-0.72	1580.2
Latino	-0.74	2.44
LGBTQ	-0.72	304.57
Liberal Ideology	-0.67	44.93
Life and Natural Science Occupations	-0.71	30.79
Male	-0.72	1506.78
Native American	-0.76	3.55
Natural Resources Occupations	-0.77	231.83
Outdoorsman/women Interests/Hobbies	-0.77	16.69
Parent	-0.74	620.67
Politics Occupations	-0.72	29.02
Pro-Environment Interests/Hobbies	-0.75	89.58
Pro-Guns Interests/Hobbies	-0.75	18.17
Religious	-0.75	133.47

Spouse	-0.77	472.87
They	-0.73	232.5
White	-0.65	3.46
Wild Pigs Interests/Hobbies	-0.57	68.17

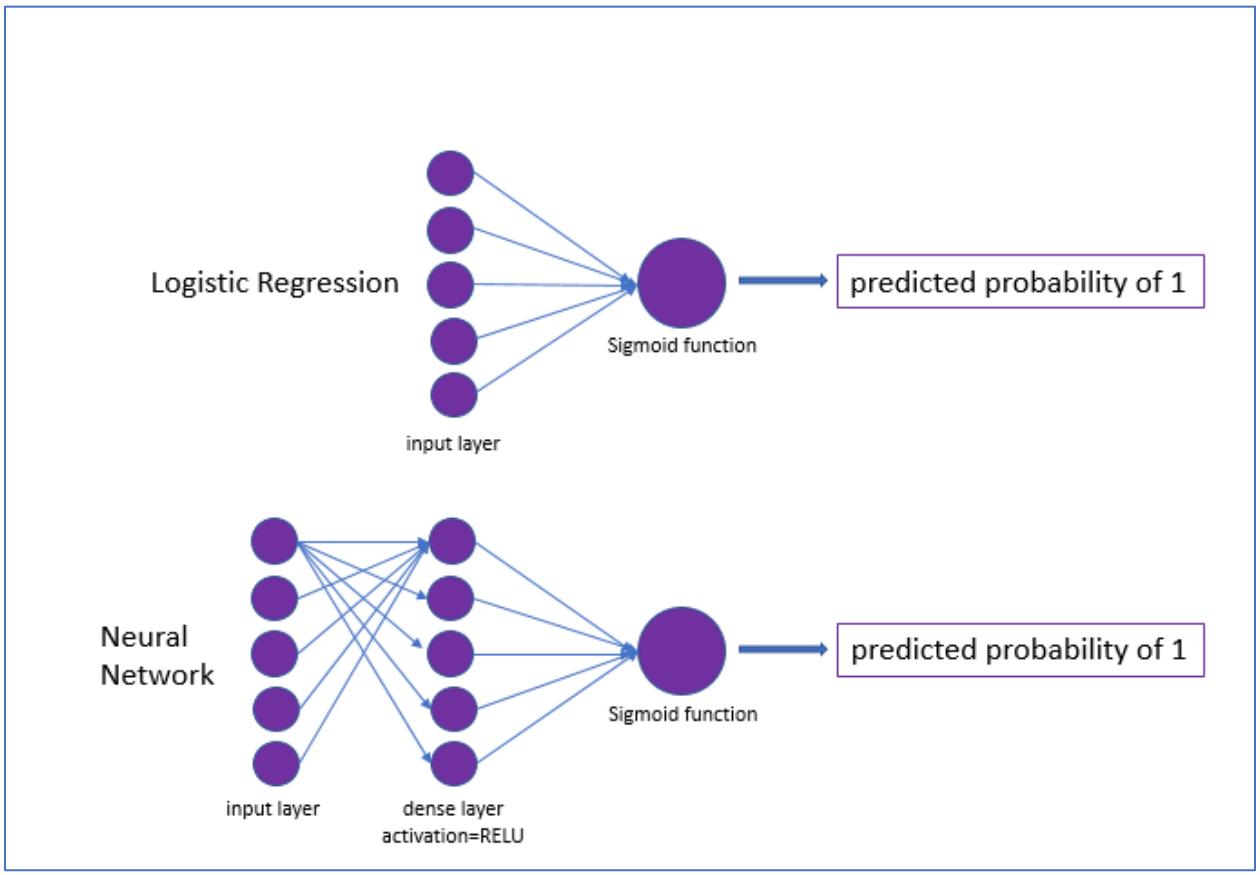

Figure 2.0 – Relating logistic regression to a simple neural network classifier

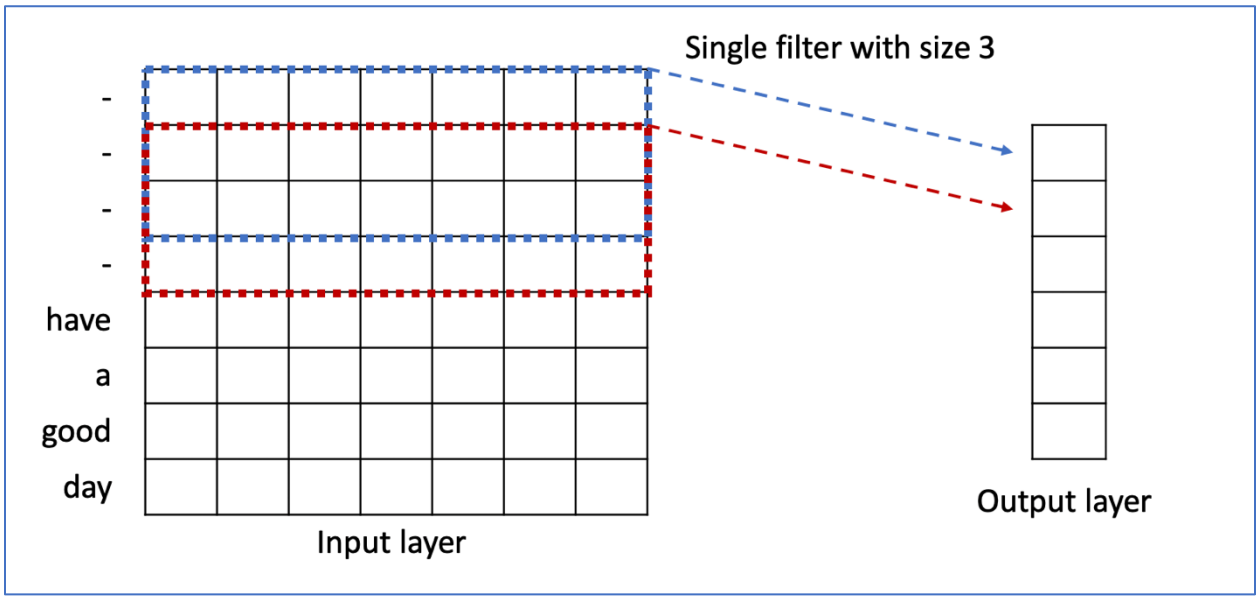

Figure 2.1 – Mapping inputs to outputs with a filter

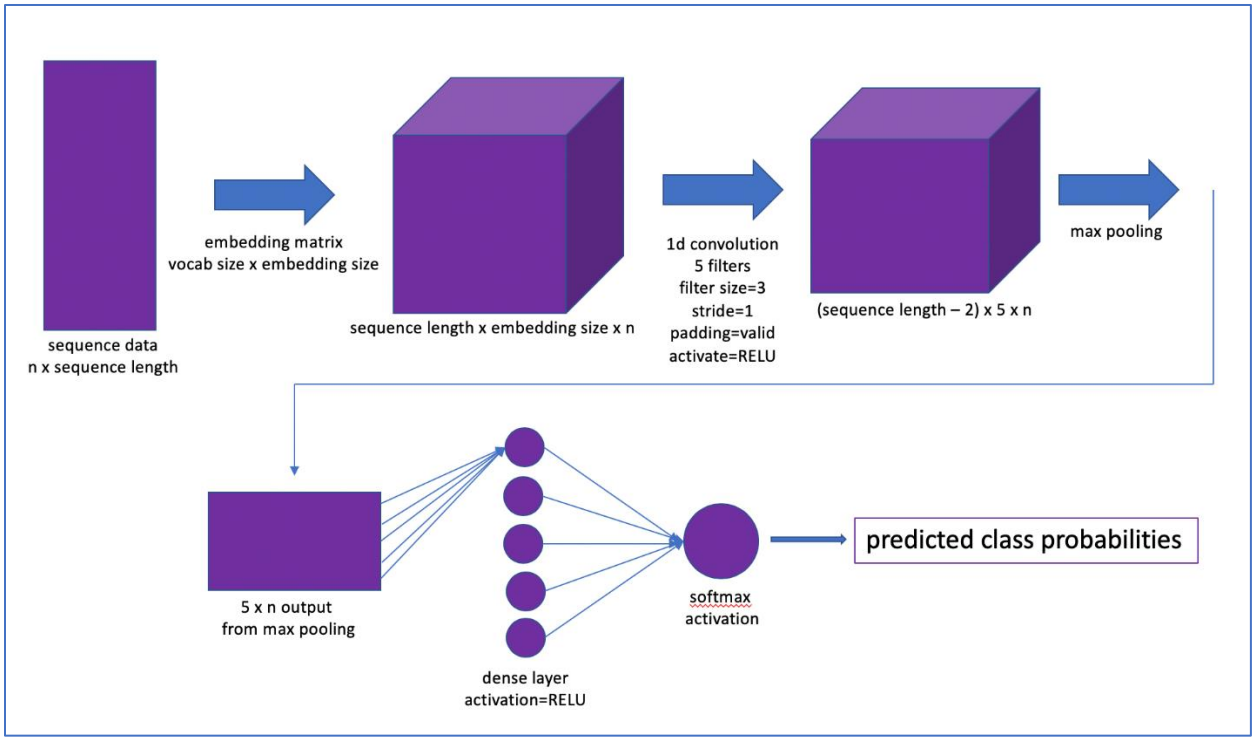

Figure 2.2 – Simplified CNN architecture

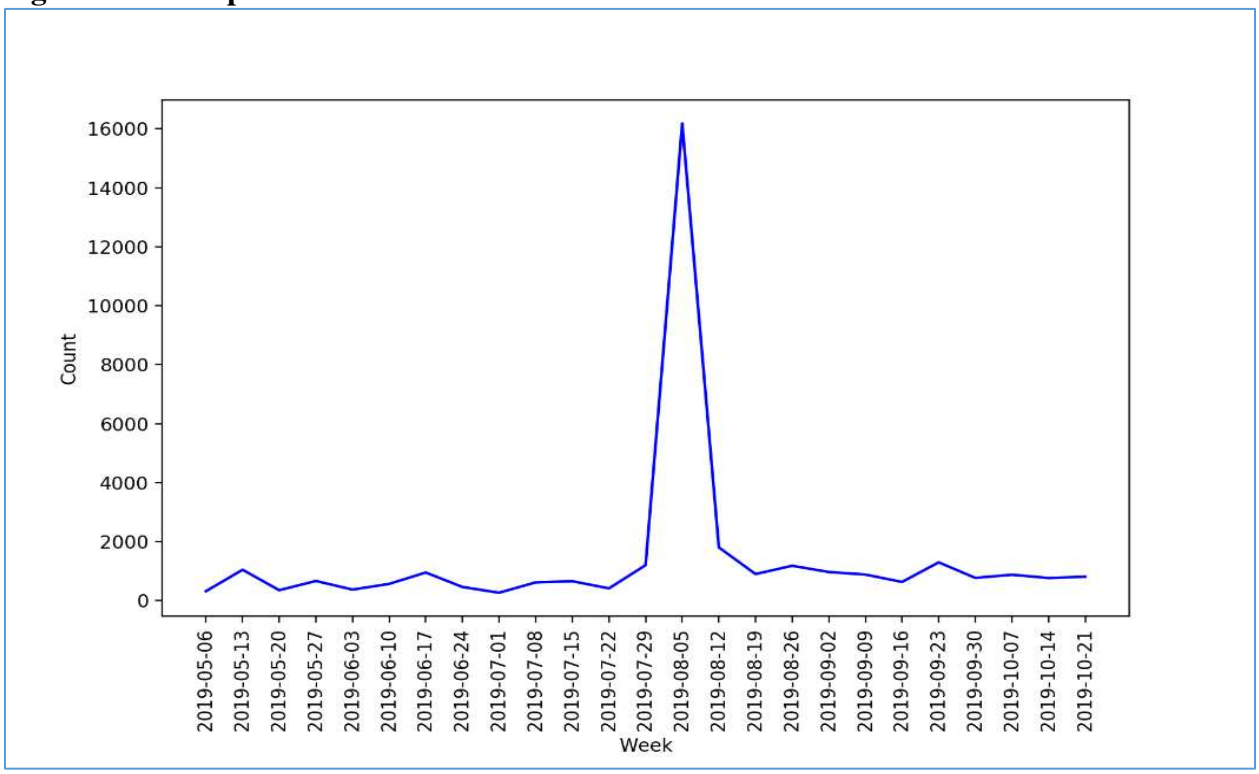

Figure 2.3 – Tweet count over time

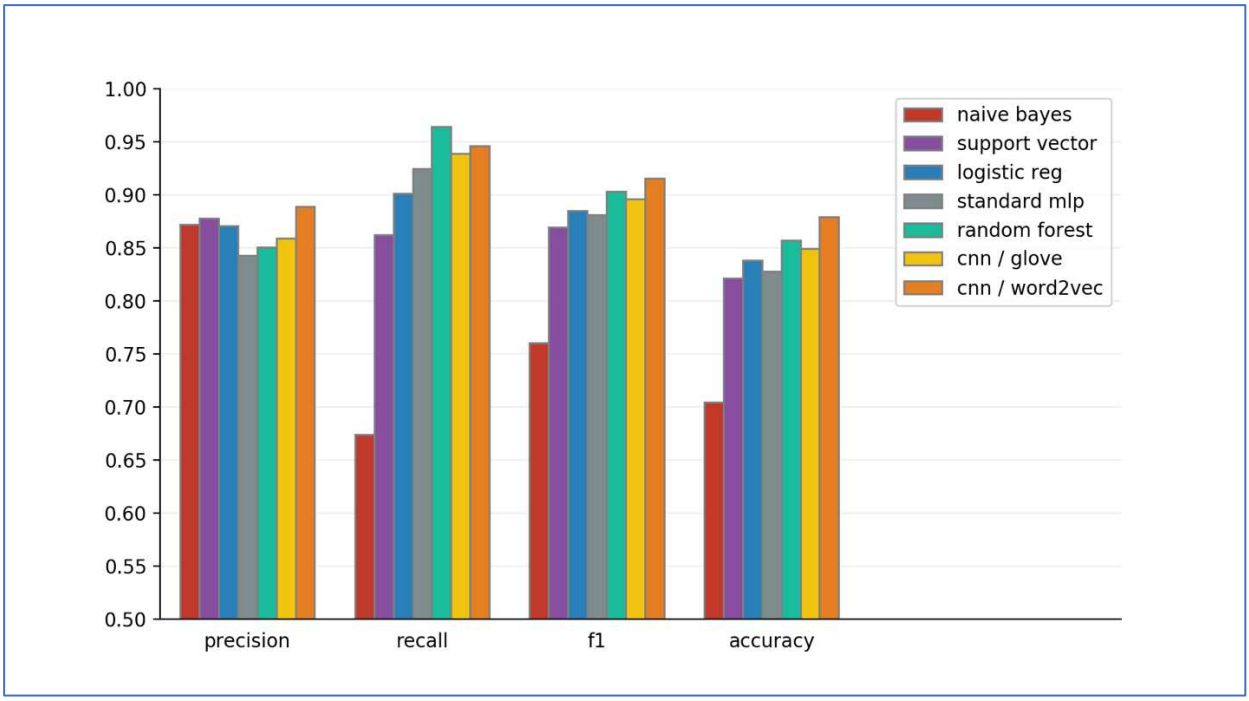

Figure 2.4 – Performance of the seven algorithms

```
Layer (type)                 Output Shape              Param #     Connected to
==================================================================================================
input_22 (InputLayer)        (None, 63)                0
__________________________________________________________________________________________________
embedding_16 (Embedding)     (None, 63, 300)           2038200     input_22[0][0]
__________________________________________________________________________________________________
conv1d_46 (Conv1D)           (None, 62, 32)            19232       embedding_16[0][0]
__________________________________________________________________________________________________
conv1d_47 (Conv1D)           (None, 61, 32)            28832       embedding_16[0][0]
__________________________________________________________________________________________________
conv1d_48 (Conv1D)           (None, 60, 32)            38432       embedding_16[0][0]
__________________________________________________________________________________________________
global_max_pooling1d_46 (Global (None, 32)             0           conv1d_46[0][0]
__________________________________________________________________________________________________
global_max_pooling1d_47 (Global (None, 32)             0           conv1d_47[0][0]
__________________________________________________________________________________________________
global_max_pooling1d_48 (Global (None, 32)             0           conv1d_48[0][0]
__________________________________________________________________________________________________
concatenate_16 (Concatenate)    (None, 96)             0           global_max_pooling1d_46[0][0]
                                                                   global_max_pooling1d_47[0][0]
                                                                   global_max_pooling1d_48[0][0]
__________________________________________________________________________________________________
dense_63 (Dense)             (None, 128)               12416       concatenate_16[0][0]
__________________________________________________________________________________________________
dropout_21 (Dropout)         (None, 128)               0           dense_63[0][0]
__________________________________________________________________________________________________
dense_64 (Dense)             (None, 1)                 129         dropout_21[0][0]
__________________________________________________________________________________________________
activation_16 (Activation)   (None, 1)                 0           dense_64[0][0]
==================================================================================================
Total params: 2,137,241
Trainable params: 99,041
Non-trainable params: 2,038,200
```

Figure 2.5 – Final CNN architecture for relevance classification

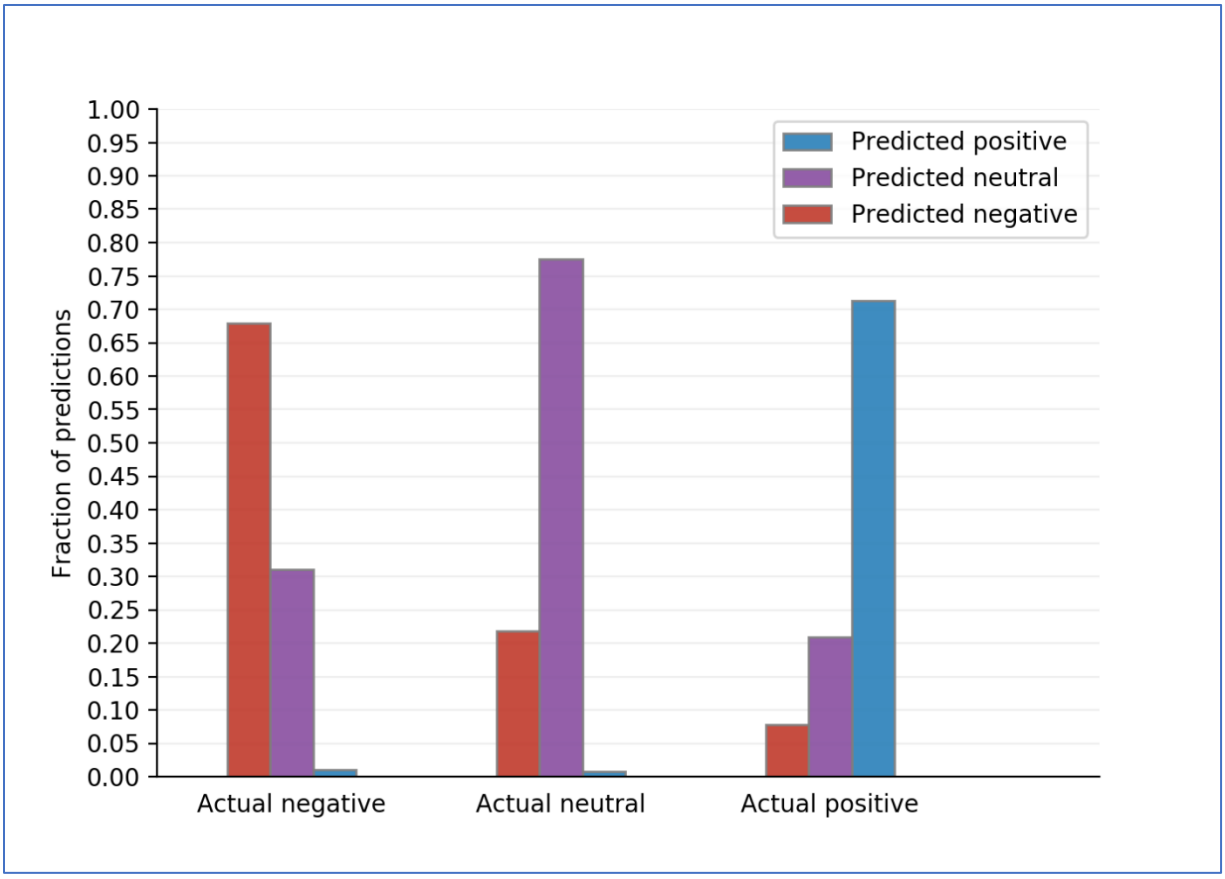

Figure 2.6 – Distribution of predicted sentiment class by true label

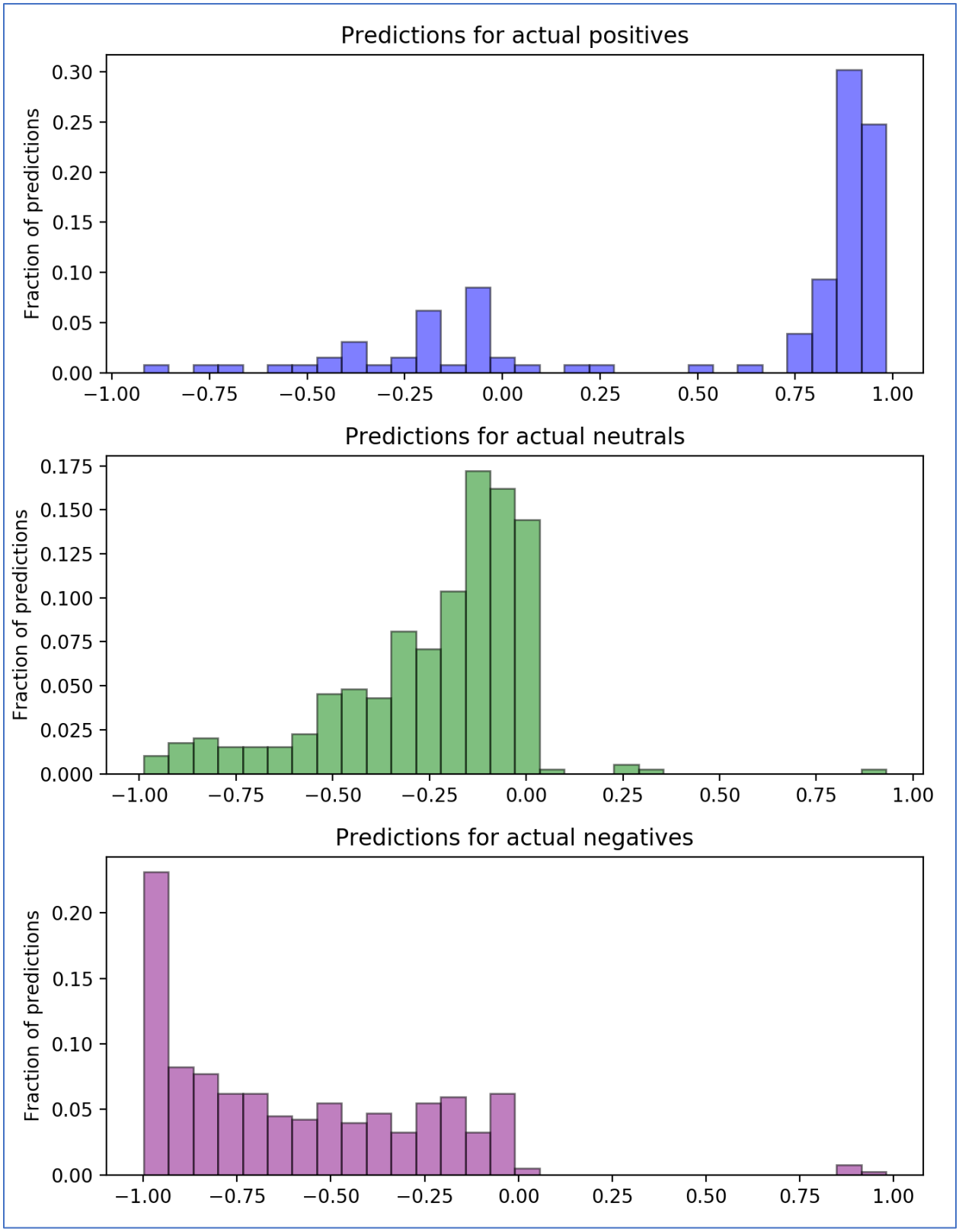

Figure 2.7 – Distribution of expected sentiment by true sentiment label

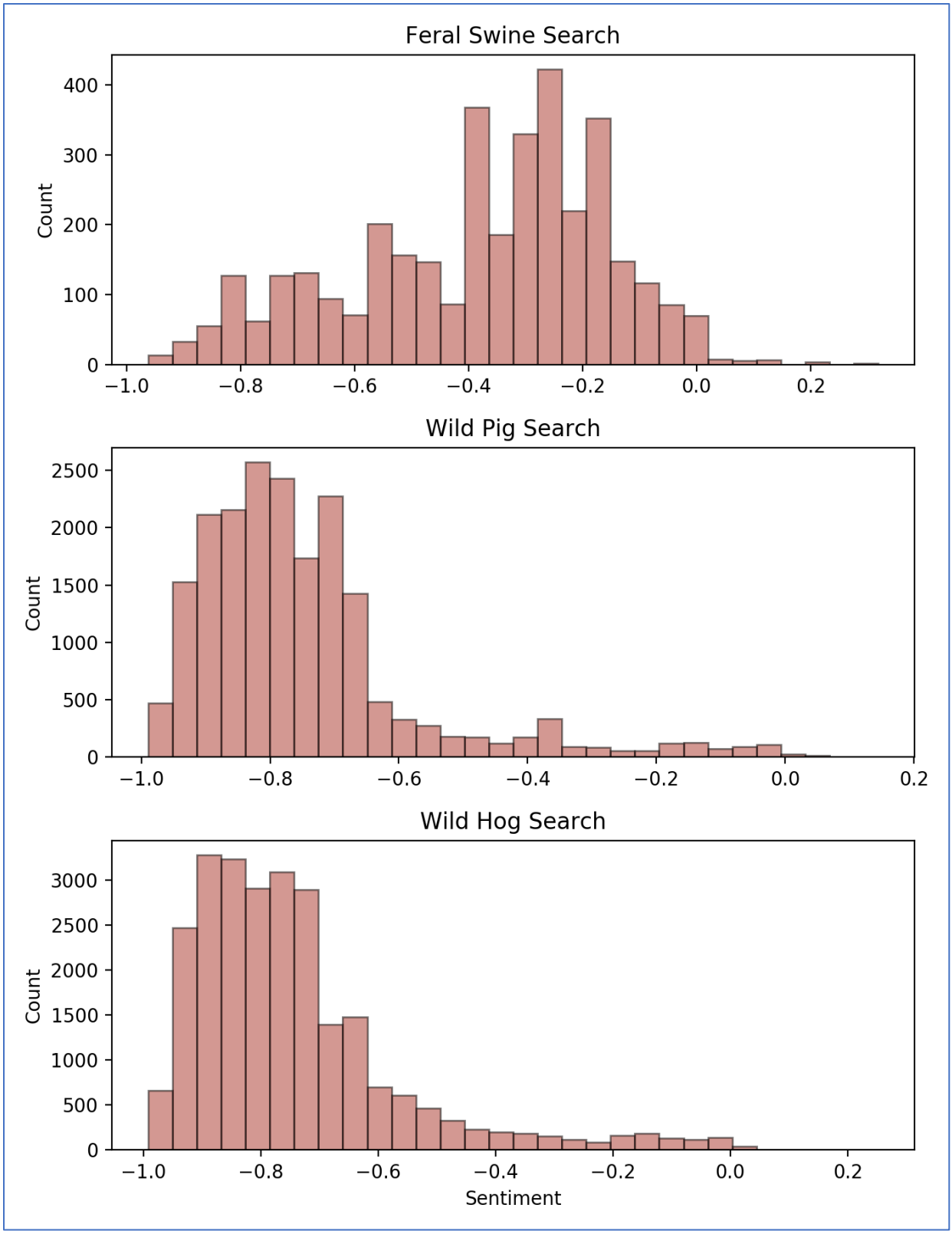

Figure 2.8 – Distribution of expected sentiment across all tweets

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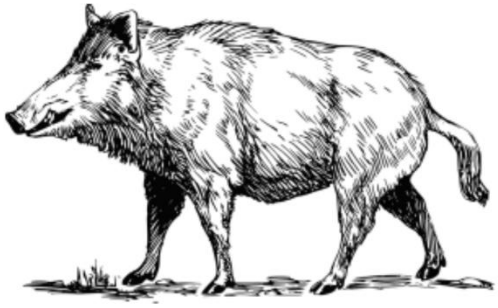
APPENDIX A: SURVEY INSTRUMENT

TEXAS A&M AGRILIFE EXTENSION

Human Dimensions of Wild Pigs
Survey Packet



Principal Investigators: Dr. John Tomeček and Dr. Maureen Frank

Welcome to the Texas A&M AgriLife Human Dimensions of Wild Pigs Survey!

We thank you for choosing to help us in our research!

You are one of a small number of participants who were randomly selected to participate in our survey. This study is designed to allow Texas A&M AgriLife Extension Service to better understand hunter, landowner, and stakeholder opinions about wild pigs and management practices for the species.

Please review the following information sheet and before proceeding to the survey.

Then, please complete the questions contained in this survey booklet and return the survey in the postage-paid return envelope provided.

In this survey, the term "wild pig" refers to any free-roaming and free-living swine. Other names for wild pigs include feral swine, feral pig, wild hog, and wild boar. The term "wild pig" does not include native wild animals, such as the collared peccary, also known as the javelina.

If you have any problems completing the survey, please contact Rachael Connally for assistance. You can reach Rachael by phone at 979-583-2205 or by email at Rachael.Connally@tamu.edu.

Your responses are important to use and we hope that you enjoy completing our survey and the chance to voice your opinions about wild pigs!

Thank you for your time and participation.

John M. Tomecek *Maureen G. Frank* *Rachael L. Connally*

John M. Tomeček, Ph.D.
Principal Investigator
Assistant Professor &
Extension Wildlife Specialist

Maureen G. Frank, Ph.D.
Co-Investigator
Assistant Professor &
Extension Wildlife Specialist

Rachael L. Connally
Graduate Research Assistant

Texas A&M University Human Research Protection Program

Information Sheet

Title of Research Study: Human Dimensions of Wild Pigs
Investigators: Dr. John Tomeček and Dr. Maureen Frank

Why am I being asked to take part in this research study?

You are invited to participate in this study because we are trying to learn more about hunter, landowner, and stakeholder opinions about wild pigs and management practices for the species.

You were selected as a possible participant in this study through a random sample of individuals within stakeholder groups, such as hunting, agricultural, and environmental interest groups. You must be 18 years of age or older to participate in this survey.

Why is this research being done?

The study is designed to allow researchers to better understand stakeholder perceptions and knowledge about wild pigs and their management in the state of Texas.

How long will the research last?

The questionnaire is expected to take approximately 30 minutes to complete.

What will I be asked to do in this study?

You will be asked to answer a series of questions about your thoughts and opinions on the resource use, economic impacts, and management of wild pigs.

What happens if I do not want to be in this research?

Your participation in this study is voluntary. You can decide not to participate in this research and it will not be held against you. You can leave the study at any time.

Are there any risks to me?

No risks are expected to participants in the study. There are no sensitive questions in this survey that should cause discomfort. However, you can skip any question you do not wish to answer, or exit the survey at any point.

Are there any benefits to me?

No benefits are expected to participants in the study.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study and other records, to people who have a need to review this information. We cannot promise complete privacy. Organizations that may inspect and copy your information include the TAMU HRPP and other representatives of this institution. No identifiers linking you to this study will be included in any sort of report that might be published.

Who can I talk to?

Please feel free to ask questions regarding this study. You may contact the Principal Investigator, John Tomeček, by phone at 325-650-3520 or by email at tomecek@tamu.edu.

For questions about your rights as a research participant; or if you have questions, complaints, or concerns about the project, you may call the Human Research Protection Program at Texas A&M University (which is a group of people who review the research to protect your rights) by phone at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu.

Section 1: Hunting

1. Do you hunt in Texas?

○ Yes ○ No

If you do not hunt in Texas, please skip to Section 2 on page 3.

2. Which types of animals do you hunt in Texas?

Please rank all that apply, with **1** being the animal you hunt **most often**.
Please include **all** animals that you hunt for both recreational and management purposes.

☐	Wild pigs	☐	Exotics (axis, black buck, fallow, elk, etc.)
☐	White-tailed deer	☐	Migratory game birds (dove, duck, goose, etc.)
☐	Mule deer	☐	Upland game birds (quail, turkey, pheasant, etc.)
☐	Javelina	☐	Other (fur-bearing animals, predators, rabbits, etc.)
☐	Pronghorn		

If you do not hunt wild pigs, please skip to Section 2 on page 3.

3. What are the most important reasons that you hunt wild pigs?

Please rate the following reasons from "not at all important" to "very important".

	Not at all important 1	Not very important 2	A little important 3	Fairly important 4	Very important 5
Meat	○	○	○	○	○
Trophies (skull, etc.)	○	○	○	○	○
Recreation	○	○	○	○	○
Controlling wild pig population	○	○	○	○	○
Controlling wild pig damage	○	○	○	○	○

4. How many wild pigs did you harvest while hunting in 2018?

☐ wild pigs

5. How many days did you spend hunting wild pigs in Texas in 2018?

☐ days

6. How many days did you spend hunting other large game animals in Texas in 2018?

Please include days that you hunted deer, exotics, and any big game animals except wild pigs.

☐ days

7. Which statement best describes the majority of your hunting trips?

- ○ I exclusively hunt wild pigs on most of my hunting trips.
- ○ I primarily hunt wild pigs, but will harvest a native game animal if I see one.
- ○ I hunt wild pigs and native game animals about equally during the same trip.
- ○ I primarily hunt native game animals, but will harvest a wild pig if I see one.
- ○ I exclusively hunt native game animals and do not hunt wild pigs on most of my hunting trips.

8. How much money did you spend on wild pig hunting-related purchases in 2018?

Please estimate the costs of the following items to a whole dollar amount.

Hunting lease(s) or access fees	$		.00 (dollars only)
Tour operator or guide fees	$		.00 (dollars only)
Overnight accommodations	$		.00 (dollars only)
Transportation	$		.00 (dollars only)
Meals	$		.00 (dollars only)
Ammunition	$		.00 (dollars only)
Bait / Attractant	$		.00 (dollars only)
Processing or taxidermy	$		.00 (dollars only)
Hunting tools / guns and accessories	$		.00 (dollars only)
Other, please specify:	$		.00 (dollars only)

_____

9. How would you describe the present size of the wild pig population in the areas where you most often hunt them?

○ Too low ○ About right ○ Too high

10. What type of property do you typically use to hunt wild pigs?

Please select all that apply.

- ☐ Personal property
- ☐ Family-owned or friend's property
- ☐ Leased property
- ☐ Property I manage
- ☐ Public land
- ☐ Private property while on a guided hunt
- ☐ Private property by landowner request
- ☐ Other, please specify:

_____

11. During which times of the year do you typically hunt wild pigs?

Please select all that apply.

- ☐ Spring
- ☐ Summer
- ☐ Fall
- ☐ Winter

12. Where do you typically hunt wild pigs?
Please select all that apply.

- ☐ Rangeland
- ☐ Agricultural fields
- ☐ Pastures
- ☐ Roads or wildlife openings
- ☐ Near artificial food sources (livestock feeders, etc.)
- ☐ Near natural or artificial water sources
- ☐ Thick brush or forests
- ☐ Other, please specify: _____

Please indicate the level to which you agree with the following statements by writing the corresponding number in each box.

		Strongly disagree 1	Somewhat disagree 2	Neither agree nor disagree 3	Somewhat agree 4	Strongly agree 5
13.	Wild pigs increase hunting opportunities for me and my family.	○	○	○	○	○
14.	I would go hunting for other animals more if wild pigs were less available to hunt.	○	○	○	○	○
15.	I prefer to hunt wild pigs even when other animals are available for me to hunt.	○	○	○	○	○
16.	Wild pigs are less enjoyable to hunt than other animals.	○	○	○	○	○
17.	I started hunting wild pigs before I became interested in hunting other animals.	○	○	○	○	○
18.	I devote more time to hunting wild pigs than other animals.	○	○	○	○	○
19.	I only purchase my hunting license to hunt wild pigs.	○	○	○	○	○

20. Which of the following personal protective equipment do you use when handling wild pigs?
Please select all that apply.

- ☐ Rubber gloves
- ☐ Protective eyewear
- ☐ Face mask
- ☐ Tick repellant
- ☐ Soap
- ☐ Knife and surface disinfectant
- ☐ Long sleeves and pants
- ☐ None
- ☐ Other, please specify: _____

Section 2: Trapping

1. What types of traps do you use for wild pigs?
Please select all that apply.

- ☐ Snares
- ☐ Cage traps
- ☐ Box traps
- ☐ Corral traps
- ☐ Figure 6 traps
- ☐ Figure "C" traps
- ☐ Drop-style traps
- ☐ I do not use any traps for wild pigs.
- ☐ Other, please specify: _____

If you do not use traps for wild pigs, please skip to Section 3 on page 4.

2. How many wild pigs did you harvest by trapping or snaring in 2018?

[ ] wild pigs

3. Have you ever trapped and sold live wild pigs?

○ Yes ○ No

If you have never trapped and sold wild pigs, please skip to Section 3 on page 4.

4. How many wild pigs did you sell in 2018?

[ ] wild pigs

5. How much income did you make by trapping and selling pigs in 2018?

$ [ ] .00 (dollars only)

6. What type of property do you typically use to trap wild pigs?

Please select all that apply.

- ☐ Personal property
- ☐ Family-owned or friend's property
- ☐ Leased property
- ☐ Property I manage
- ☐ Public land
- ☐ Private property while on a guided hunt
- ☐ Private property by landowner request
- ☐ Other, please specify: _____

7. During which times of the year do you typically trap wild pigs?

Please select all that apply.

- ☐ Spring
- ☐ Summer
- ☐ Fall
- ☐ Winter

8. Where do you typically trap wild pigs?

Please select all that apply.

- ☐ Rangeland
- ☐ Agricultural fields
- ☐ Pastures
- ☐ Roads or wildlife openings
- ☐ Near artificial food sources (livestock feeders, etc.)
- ☐ Near natural or artificial water sources
- ☐ Thick brush or forests
- ☐ Other, please specify: _____

Section 3: Guide Services

1. Did you provide any wild pig guide or outfitting services to paying hunters in 2018?

○ Yes ○ No

If you did not provide these services, please skip to Section 4 on page 5.

2. How much income did you make by providing wild pig guide or outfitting services to paying hunters in 2018?

$ [ ] .00 (dollars only)

Section 4: Land Management

1. Do you own or manage land in Texas?

○ Yes ○ No

If you do not own land in Texas, please skip to Section 5 on page 6.

2. What are the uses of the land you own or manage in Texas?

Please rank all that apply by importance, with **1** being the **most important**.

☐	Private residence	☐	Personal recreation (hunting, fishing, leisure, etc.)
☐	Farming or crop production	☐	Lease hunting (include guide services, outfitting, etc.)
☐	Ranching - Domestic livestock	☐	Natural gas or oil extraction
☐	Ranching – Native wildlife (deer, quail, etc.)	☐	Timber production
☐	Ranching – Exotic wildlife	☐	Other, please specify: _____

3. What is the size of the largest property you own or manage in Texas?

☐ acres

4. Please mark all of the areas in which wild pigs had negative impacts on your property in the past year.

☐	Growing or planting commodity crop losses	☐	Fences, water troughs, or other improvements
☐	Growing or planting specialty crop losses	☐	Equipment or vehicles
☐	Stored Commodities	☐	Personal injuries
☐	Pastures	☐	Loss of land value
☐	Wetlands	☐	Loss of lease value, damage to food plots/feeders
☐	Livestock (injury, deaths, diseases)	☐	Owner or employee time

5. Please mark all of the control methods you use on your property(s).

☐	Trapped & destroyed	☐	Owner/Employee hunting	☐	Use of snares
☐	Trapped & moved from premise	☐	Lease hunting	☐	Aerial shooting
☐	Trapped & sold	☐	Use of dogs	☐	Other

6. Please estimate your total economic losses due to wild pigs in 2018 on all your property(s).

$ ☐ .00 (dollars only)

7. How much income did you make by leasing wild pig hunting rights in 2018?

$ ☐ .00 (dollars only)

Section 5: Attitudes, Knowledge, and Perceptions

1. What change would you like to see in wild pig population numbers in the state of Texas?

○ Completely removed ○ Reduced ○ Remain the same ○ Increase ○ I do not know.

2. Which of the following types of wild pig control methods do you think are, or would be, **effective**?

Please indicate the level of effectiveness for each method on the scale below.

	Completely ineffective 1	Somewhat ineffective 2	Neutral 3	Somewhat effective 4	Completely effective 5
Trap and lethally remove	○	○	○	○	○
Trap and sell	○	○	○	○	○
Use of a safe, humane toxicant	○	○	○	○	○
Use of dogs	○	○	○	○	○
Use of snares	○	○	○	○	○
Non-lethal deterrents	○	○	○	○	○
Lease hunting	○	○	○	○	○
Owner/employee hunting	○	○	○	○	○
Government or agency hunting	○	○	○	○	○
Aerial shooting	○	○	○	○	○

3. Which of the following types of wild pig control methods are, or would be, personally **acceptable** to you?

Please indicate the level of acceptability for each method on the scale below.

	Completely unacceptable 1	Somewhat unacceptable 2	Neutral 3	Somewhat acceptable 4	Completely acceptable 5
Trap and lethally remove	○	○	○	○	○
Trap and sell	○	○	○	○	○
Use of a safe, humane toxicant	○	○	○	○	○
Use of dogs	○	○	○	○	○
Use of snares	○	○	○	○	○
Non-lethal deterrents	○	○	○	○	○
Lease hunting	○	○	○	○	○
Owner/employee hunting	○	○	○	○	○
Government or agency hunting	○	○	○	○	○
Aerial shooting	○	○	○	○	○

4. Please indicate your level of concern for the following types of damage caused by wild pigs.

	No concern 1	Low level of concern 2	Moderate level of concern 3	High level of concern 4	Very high level of concern 5
Crop losses	○	○	○	○	○
Stored commodity losses	○	○	○	○	○
Damage to pastures	○	○	○	○	○
Damage to wetlands	○	○	○	○	○
Habitat degradation	○	○	○	○	○
Damage to water quality	○	○	○	○	○
Damage to personal property	○	○	○	○	○
Loss of land value	○	○	○	○	○
Loss of lease value	○	○	○	○	○
Livestock injury or disease	○	○	○	○	○
Wildlife competition or predation	○	○	○	○	○
Human disease or injury	○	○	○	○	○

Based on your current knowledge of wild pigs, please mark each of the following statements as either true or false.

		True	False	I am unsure.
5.	Wild pigs can carry diseases that can be spread to domestic animals.	○	○	○
6.	Wild pigs are native to Texas.	○	○	○
7.	Wild pigs can carry diseases that can be spread to humans.	○	○	○
8.	Wild pigs are a different species than domestic pigs.	○	○	○
9.	Wild pigs can breed year-round in Texas.	○	○	○
10.	Wild pigs have an average of 12 piglets per litter.	○	○	○
11.	Wild pigs kill livestock and wildlife as a primary source of food.	○	○	○
12.	Wild pigs are present in less than 70% of Texas counties.	○	○	○
13.	Wild pigs are regulated as a game animal in the state of Texas.	○	○	○
14.	There are legal restrictions on the transportation, release, and holding of live wild pigs in Texas.	○	○	○

15. How has each of the following affected the number of wild pigs in the county where you live?

	Substantially Decreased 1	Somewhat Decreased 2	No Change 3	Somewhat Increased 4	Substantially Increased 5	I am unsure.
Hunting of wild pigs	○	○	○	○	○	○
Neighbor's agriculture practices	○	○	○	○	○	○
Trapping of wild pigs	○	○	○	○	○	○
Predators	○	○	○	○	○	○
Release or escape of domestic pigs	○	○	○	○	○	○
Release or transfer of wild pigs for hunting	○	○	○	○	○	○
Natural movement of wild pigs	○	○	○	○	○	○
Availability of food sources for wild pigs	○	○	○	○	○	○
Absentee landowners	○	○	○	○	○	○

Please indicate the level to which you agree with the following statements by writing the corresponding number in each box.

		Completely disagree 1	Somewhat disagree 2	Neither agree nor disagree 3	Somewhat agree 4	Completely agree 5
16.	Wild pigs increase my overall quality of life.	○	○	○	○	○
17.	The harm caused by wild pigs outweighs any benefits of having them in Texas.	○	○	○	○	○
18.	Wild pigs are a valuable resource for recreation, meat, or income in Texas.	○	○	○	○	○
19.	Wild pigs do not belong in Texas.	○	○	○	○	○
20.	Overall, my feelings about wild pigs in Texas are generally positive	○	○	○	○	○
21.	Wild pigs are a nuisance.	○	○	○	○	○
22.	Wild pigs have the right to exist wherever they may occur.	○	○	○	○	○
23.	It should be legal to release live wild pigs anywhere in Texas in order to hunt them.	○	○	○	○	○
24.	It should be legal to transport live feral hogs anywhere in the U.S. without restrictions.	○	○	○	○	○
25.	I would feel comfortable using a safe, humane toxicant to control wild pig populations.	○	○	○	○	○
26.	I would feel comfortable consuming the meat of a wild pig if safe, humane toxicants were used near where the animal was harvested.	○	○	○	○	○

27. Please tell us more about your position on a safe, humane toxicant for wild pigs.

Section 6: AgriLife Educational Outreach

1. Have you ever attended an AgriLife educational seminar on wild pigs?

○ Yes ○ No ○ I am not sure.

If you have not attended an AgriLife educational seminar on wild pigs, please skip to Section 7 on page 10.

2. Please mark all practices that you planned to adopt, adopted, and continue to use in order to better manage wild pigs on your property after attending an AgriLife educational seminar.

	Planned to adopt	Adopted	Continue to use
Use larger traps	☐	☐	☐
Use baits with scent appeal	☐	☐	☐
Vary/change baits at different locations	☐	☐	☐
Set traps whenever fresh sign appears	☐	☐	☐
Pre-bait traps to encourage consistent pig visits	☐	☐	☐
Scout for pig sign (tracks, wallows, rubs, hair)	☐	☐	☐
Wear eyewear and gloves during field dressing	☐	☐	☐
Market trapped pigs to processors to recoup losses	☐	☐	☐

3. Please indicate the reasons why you do not continue to use the suggested practices that you adopted following an AgriLife education seminar.

Please check all that apply.

☐ Financial expenses

☐ Time expenses

☐ Physical difficulties

☐ Confusion due to lack of information

☐ Not applicable on my property

☐ I am unconcerned about wild pigs on my property.

☐ I found these practices unimportant.

☐ I saw no results using these methods.

☐ I still employ all methods that I initially intended to employ.

☐ Other, please specify:

_____

Section 7: Information Sources

1. What AgriLife Extension Service resources have you used to learn about wild pigs?

Please select all that apply.

- ☐ Communication with AgriLife Extension agents
- ☐ Educational seminars
- ☐ Social media
- ☐ Online videos
- ☐ Articles or publications
- ☐ Webinars
- ☐ I have not used any AgriLife resources.
- ☐ Other, please specify: _____

2. What other resources have you used to learn about wild pigs?

Please select all that apply.

- ☐ Communication with state wildlife professionals (TPWD)
- ☐ Educational seminars
- ☐ Local newspaper or news broadcast
- ☐ Social media (Facebook, Twitter, Instagram, etc.)
- ☐ Online videos
- ☐ Communication with federal wildlife professionals (APHIS, USDA, USFWS, etc.)
- ☐ Communication with other hunters, landowners, farmers, or ranchers
- ☐ Articles or publications
- ☐ Hunting or wildlife magazines
- ☐ I have not used any other resources.
- ☐ Other, please specify: _____

3. Which of the following best describes why you use social media for wild pig hunting content?

Please select only one.

- ○ To learn new hunting techniques
- ○ To get ideas about where to hunt
- ○ To watch wild pigs get harvested
- ○ To learn about wild pigs
- ○ To be entertained
- ○ To remind me of my memorable hunts

If you do not watch wild pig hunting videos, please skip to question number 4.

4. What resources would you trust to learn about methods to manage or control wild pigs?

Please select all that apply.

- ☐ Communication with state wildlife professionals (TPWD)
- ☐ Communication with AgriLife Extension agents
- ☐ Educational seminars
- ☐ Local newspaper or news broadcast
- ☐ Social media (Facebook, Twitter, Instagram, etc.)
- ☐ Online videos
- ☐ Communication with federal wildlife professionals (APHIS, USDA, USFWS, etc.)
- ☐ Communication with other hunters, landowners, farmers, or ranchers
- ☐ Articles or publications
- ☐ Hunting or wildlife magazines
- ☐ None
- ☐ Other, please specify: _____

Section 8: Demographic Information

To help us better understand how to share educational information and knowledge on wild pigs in the future, please answer the following questions about yourself.

1. What is your ZIP code of primary residence?

Please enter your 5-digit ZIP code, such as "77843"

2. In what year were you born?

Please enter your 4-digit birth year, such as "1965"

3. What is your gender?

- ○ Male
- ○ Female

4. What is the highest level of education you have obtained?

- ○ Did not graduate high school or receive GED
- ○ High school graduate, diploma or GED
- ○ Some college, no degree
- ○ Associate degree
- ○ Trade/technical/vocational training
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree

5. Please specify your ethnicity.

- ○ White
- ○ Black or African American
- ○ American Indian or Alaska Native
- ○ Spanish, Hispanic, or Latino
- ○ Asian
- ○ Native Hawaiian or Pacific Islander
- ○ Other

6. Please indicate your average household income.

- ○ Less than $20,000
- ○ $20,000 to $34,999
- ○ $35,000 to $49,999
- ○ $50,000 to $74,999
- ○ $75,000 to $99,999
- ○ Over $100,000

7. From the list below, please select all of the wildlife, environmental, or agricultural interest groups of which you are a member.

- ☐ Texas Farm Bureau
- ☐ Texas and Southwestern Cattle Raisers Association
- ☐ Texas Sheep and Goat Raisers Association
- ☐ Texas Pork Producers
- ☐ Texas Hog Hunters' Association
- ☐ Quail Forever
- ☐ Ducks Unlimited
- ☐ Exotic Wildlife Association
- ☐ Texas Wildlife Association
- ☐ Dallas Safari Club
- ☐ Audubon Society
- ☐ Texas Ornithological Society
- ☐ Texas Master Naturalists
- ☐ Native Plant Society of Texas
- ☐ The Nature Conservancy
- ☐ Texas Land Conservancy
- ☐ Texas Corn Producers
- ☐ Texas Cotton Association
- ☐ Texas Pecan Growers Association
- ☐ Texas Forestry Association
- ☐ Texas Trophy Hunters Association
- ☐ Pheasants Forever
- ☐ National Turkey Federation (Texas Chapter)
- ☐ Texas Deer Association
- ☐ Texas Dove Hunters Association
- ☐ Houston Safari Club
- ☐ Lone Star Chapter of the Sierra Club
- ☐ Texas Master Gardeners
- ☐ Native Prairies Association of Texas
- ☐ Big Thicket Association
- ☐ Environment Texas
- ☐ I am not a member of any of wildlife, environmental, or agricultural groups.
- ☐ Other, please specify _____

8. If you have any comments you would like to leave about this survey, please write them here.

Thank you for completing our survey!

We appreciate your time and contributions to our research.

Please return this questionnaire in the enclosed postage-paid envelope.

Should you have any questions or comments regarding this survey, please contact Rachael Connally by email at rachael.connally@tamu.edu or by phone at 979-583-2205.

Thanks again,

John M. Tomecek

John M. Tomeček, Ph.D.
Principal Investigator
Assistant Professor &
Extension Wildlife Specialist

Maureen G. Frank

Maureen G. Frank, Ph.D.
Co-Investigator
Assistant Professor &
Extension Wildlife Specialist

Rachael L. Connally

Rachael L. Connally
Graduate Research Assistant

APPENDIX B: IDENTITY CODEBOOK

Broader Code	Finer Code	Explanation
Occupations	Armed Forces	Army, United States Air Force, Marine, Coast Guard (retired or active duty)
	Agriculture	Farmer, Rancher
	Computer Science	Computer Technician, Information Technology, Data Scientist, Programmer, Web Developer
	Engineering	Chemical, Biological, Computer, Civil, Mechanical
	Natural Sciences	Biologist, Chemist, Geologist, Physicist, Microbiologist, Meteorologist, Physical Scientist
	Academic	Teacher, PhD, Student, Professor, Researcher
	Healthcare	Nurse, Medical Doctor, Therapist, Psychologist
	Business Administrative	Accountant, Financial Planner, Human Resources, Information Systems, Marketing, Real Estate Agent, Director, CEO, CFO
	Art	Drawing, Graphic Designer, Painter, Print Making, Interior Architect, Landscape Architect
	Journalism & Media Communication	Writer, Editor, Author, News, News Reporter, Radio (host), Reporter
	Legal	Lawyer, Attorney
	Natural Resources	Conservationist, Environmentalist, Wildlife Ecologist, Fisheries & Aquatic Scientist, Entomologist, Forester, Horticulturalist

	History & Cultural Studies	Historian, Anthropologist, Genealogist, Paleontologist, Archeologist, Archivist, Library Scientist
	Sports	Athlete, Coach
	Thespians	Comedian, Performer
	Animal Science	Veterinarian
	Criminal Justice/Political Science	Police officer, Investigator
	Other	Trades, other
Gender	Male, He, Him, man	Any persons who used the finer code terms directly within their user descriptions
	Female, She, Her, woman	Any persons who used the finer code terms directly within their user descriptions
	Transgender	Any persons who used the finer code terms directly within their user descriptions
	They, Them	Any persons who used the finer code terms directly within their user descriptions
Spouse	Married	Any persons who used the finer code terms directly within their user descriptions
	Husband	Any persons who used the finer code terms directly within their user descriptions
	Wife	Any persons who used the finer code terms directly within their user descriptions
Parent/Grandparent	Parent	Any persons who used the finer code terms directly within their user descriptions

	Mom/Mother	Any persons who used the finer code terms directly within their user descriptions
	Dad/Father	Any persons who used the finer code terms directly within their user descriptions
	Grandma/mother	Any persons who used the finer code terms directly within their user descriptions
	Grandpa/father	Any persons who used the finer code terms directly within their user descriptions
Political Affiliation	Republican, (Pro) Conservative, Anti-Liberal, Right	Any persons who used the finer code terms directly within their user descriptions
	Democrat, (Pro) Liberal, Anti-Conservative, Left	Any persons who used the finer code terms directly within their user descriptions
	Libertarian	Any persons who used the finer code terms directly within their user descriptions
	Socialist	Any persons who used the finer code terms directly within their user descriptions
	Centrist	Any persons who used the finer code terms directly within their user descriptions
Religious Affiliation	Christian	Any persons who used the finer code terms directly within their user descriptions
	Muslim	Any persons who used the finer code terms directly within their user descriptions

	"Religious"/ "In God We Trust"/ "Bible Verse"	Any persons who used the finer code terms directly within their user descriptions
	Catholic	Any persons who used the finer code terms directly within their user descriptions
	Buddhist	Any persons who used the finer code terms directly within their user descriptions
	Lutheran	Any persons who used the finer code terms directly within their user descriptions
	Atheist	Any persons who used the finer code terms directly within their user descriptions
	Other	Any persons who used the finer code terms directly within their user descriptions
Sexual Orientation	Gay	Any persons who used the finer code terms directly within their user descriptions
	Bi-sexual	Any persons who used the finer code terms directly within their user descriptions
	Queer	Any persons who used the finer code terms directly within their user descriptions
	Lesbian	Any persons who used the finer code terms directly within their user descriptions
	Straight	Any persons who used the finer code terms directly within their user descriptions

	Pansexual	Any persons who used the finer code terms directly within their user descriptions
	Asexual	Any persons who used the finer code terms directly within their user descriptions
Ethnicity	Latino	Any persons who used the finer code terms directly within their user descriptions
	Black/African	Any persons who used the finer code terms directly within their user descriptions
	White	Any persons who used the finer code terms directly within their user descriptions
	Asian	Any persons who used the finer code terms directly within their user descriptions
	European	Any persons who used the finer code terms directly within their user descriptions
	Native American/ Indigenous	Any persons who used the finer code terms directly within their user descriptions
Interests/Hobbies	Animal Lover/Advocate	Any persons who used the finer code terms directly within their user descriptions
	Blogger	Any persons who used the finer code terms directly within their user descriptions
	Geek/Nerd	Any persons who used the finer code terms directly within their user descriptions

	Vegan/Vegetarian	Any persons who used the finer code terms directly within their user descriptions
	American	Any persons who used the finer code terms directly within their user descriptions
	Texan	Any persons who used the finer code terms directly within their user descriptions
	Gear	Any persons who used the finer code terms directly within their user descriptions
	Outdoorsman/woman	Any persons who used the finer code terms directly within their user descriptions
	Canadian	Any persons who used the finer code terms directly within their user descriptions
	Angler	Any persons who used the finer code terms directly within their user descriptions
	Hunter	Any persons who used the finer code terms directly within their user descriptions
	Sports	Any persons who used the finer code terms directly within their user descriptions
	Politics	Any persons who used the finer code terms directly within their user descriptions
	Science	Any persons who used the finer code terms directly within their user descriptions

	Feminism/ist	Any persons who used the finer code terms directly within their user descriptions
	Coffee	Any persons who used the finer code terms directly within their user descriptions
	Movies/Books	Any persons who used the finer code terms directly within their user descriptions
	Gamer	Any persons who used the finer code terms directly within their user descriptions
	Humanist	Any persons who used the finer code terms directly within their user descriptions
	Pro-Climate/Environmentalist/Pro-Earth/Nature	Any persons who used the finer code terms directly within their user descriptions
	Pro-Life	Any persons who used the finer code terms directly within their user descriptions
	Family	Any persons who used the finer code terms directly within their user descriptions
	Pro-Gun	Any persons who used the finer code terms directly within their user descriptions
	Anti-Climate/Environmentalist	Any persons who used the finer code terms directly within their user descriptions
	Music	Any persons who used the finer code terms directly within their user descriptions

	Wild Pigs	Any persons who used the finer code terms directly within their user descriptions
	Food	Any persons who used the finer code terms directly within their user descriptions
	Art	Any persons who used the finer code terms directly within their user descriptions
Memberships/Government Affiliations	NRA	Any persons who used the finer code terms directly within their user descriptions
	USDA	Any persons who used the finer code terms directly within their user descriptions
	NRCS	Any persons who used the finer code terms directly within their user descriptions
	WS	Any persons who used the finer code terms directly within their user descriptions
	University Affiliate	Any persons who used the finer code terms directly within their user descriptions
Age	Variable	
Location	Variable	

APPENDIX C: ONLINE IDENTITY CATEGORIES – COLLAPSED

ONLINE IDENTITY CATEGORIES – COLLAPSED

Sociodemographic, Hobbies, Interests & Other

- Parent = 'Mom, Mother', 'Dad,Father', 'Grandma/mother','Grandpa/father', 'Parent'
- Spouse = 'Married', 'Husband', 'Wife'
- Male = 'Male, He,Him, man'
- Female = 'Female, She, Her, woman'
- They = 'They, Them'
- Conservative Ideology = 'Republican, (Pro) Conservative, Anti-Liberal, Right'
- Liberal Ideology = 'Democrat, (Pro) Liberal, Anti-Conservative, Left'
- White = 'White'
- Asian = 'Asian'
- Native American = 'Native American'
- Black/African American = 'Black/African'
- Latino = 'Latino'
- LGBTQ = 'Gay', 'Lesbian ', 'Transgender', 'Bi-sexual', 'Queer'
- Religious = '"Religious"/ "In God We Trust"/ "Bible Verse"', 'Christian ', 'Catholic'
- Pro-Environment = 'Pro-Climate/Environmentalist/Pro-Earth/Nature'
- Anti-Environment = 'Anti-Climate/Environmentalist'
- Animal Advocate = 'Animal Lover/Advocate', 'Vegan/Vegetarian '
- Outdoorsman/women = 'Outdoorsman/woman', 'Angler', 'Hunter'
- Pro-Guns = 'NRA', 'Pro-Gun'
- Politics = 'Politics'
- Government Organizations = 'USDA','NRCS', 'WS'
- Wild pigs = 'Wild Pigs'

<u>Occupations</u>

- Academic = 'University Affiliate ', 'Academic'
- Business and Computers = 'Business Admin', 'Computer Science',
- Criminal Justice, Political Science, and Legal Aid = 'Criminal Justice/Political Science ', ' Legal'
- Journalism and Media Communication = 'Journalism and Media Communication'
- Life & Natural Science = 'Natural Sciences', 'Animal Science'
- Healthcare = 'Health Care'
- Armed Forces = 'Armed Forces'
- Natural Resources = 'Natural Resources'
- Agriculture = 'Agriculture'