Mixed emotions associated with orca (Orcinus orca) conservation strategies

Hailey Kehoe Thommen | Karin Swarbrick | Kelly Biedenweg

Department of Fisheries and Wildlife, Oregon State University, Corvallis, Oregon

Correspondence
Kelly Biedenweg, Department of Fisheries and Wildlife, Oregon State University, Corvallis, OR.
Email: kelly.biedenweg@oregonstate.edu

Abstract
Orcas (Orcinus orca) are a charismatic species with multiple connections to local economies and culture in the Pacific Northwest. As such, emotions play a role in public perspectives and support for their conservation. This research presents the use of Natural Language Processing (NLP) emotion analysis to identify the basic emotions associated with written public responses to orca conservation proposals. We operationalized a multi-dimensional emotion lexicon using Python 3 programming to extract the frequency and density of each basic emotion in over 17,000 public comments specific to orca conservation submitted to the Washington state governor's office. We found that respondents held a mixture of emotions. Trust was most often associated with the belief that urgent actions by state government could help orca populations, joy was most associated with statements reflecting how healthy orcas are icons for healthy ecosystems upon which all depend, and sadness was associated with statements lamenting the death of individual orcas and population extinction. These results can help conservation managers understand why people might support or reject conservation actions and move past conservation social science that has prioritized the emotional domain of fear. Moreover, NLP provides descriptive emotion analyses of big text datasets within specific conservation contexts that can be further explored through qualitative analyses.

KEYWORDS
emotion analysis, natural language processing, orca conservation

1 | INTRODUCTION

1.1 | Conservation context

Orcas (Orcinus orca) are the largest and most widely distributed member of the Delphinidae family (Ford, 2009). Since 1996, Southern Resident orca populations have experienced steady decline (NMFS, 2002) and were listed as endangered in 2005 (United States, 1973). The most critical issues to their recovery are pollution, vessel disturbance, and prey availability (Ford, Ellis, Olesiuk, & Balcomb, 2010; Lusseau, Bain, Williams, & Smith, 2009). Orcas have captured human attention for their complex behaviors and social structure (Ford, 2009). As an icon of the Pacific Northwest they are depicted in Indigenous art, featured on license plates, and are a highlight of local
nature tourism (Ford, Ellis, & Balcomb, 1996; Jones, 2013; Ruby & Brown, 1981). In 2018, Washington governor Jay Inslee created a task force to develop recommendations for orca recovery (WA Exec Order No. 18-02, 2018). Over a period of 10 months, from July 2018 through May 2019, the governor’s office received more than 17,000 public comments regarding orca conservation. This study analyzes the basic emotions associated with those public responses using natural language processing, and describes the implications for conservation decision processes.

### 1.2 Emotion theory

Emotions are intertwined in our decision making (Angie, Connelly, Waples, & Klgyte, 2011; Charpentier, De Neve, Li, Roiser, & Sharot, 2016), often playing a substantive role in public evaluations of conservation policies. The major branches of psychology agree that the term “emotion” refers to subconscious, affective responses to significant situations. These emotions contribute to meaning making, action taking, and communication with and influence others (Feldman Barrett, 2017; LeDoux, 1998; Plutchik, 1994). Many think of the terms emotion, affect, sentiment and valence as synonymous. We use the accepted definition of emotion as laid out above, whereas affect is a more general and encompassing state of feeling, and sentiments are feelings that can be measured as positive–negative valence or polarity (Feldman Barrett, 2017; Liu, 2015; Straka et al., 2020). Emotion analysis, therefore, specifically focuses on categorizing or quantifying emotional content (e.g., happiness, fear, and anger) whereas sentiment analysis reflects the positive or negative polarity of a statement.

Some psychologists have described basic emotions, such as “happy” and “angry”, as discrete, often having a set of distinctive characteristics, such as universal signals, physiology, antecedent events, quick onset, and brief duration (e.g., Ekman, 1992; Izard, 2007). Others have clarified that the there are no specific physiological “fingerprints” for basic emotions; rather, they are constructed by our brains to respond to our context in a way that is consistent with our cultural upbringing (e.g., Feldman Barrett, 2017). Since the 1600s, scientists have attempted to identify a full suite of human emotions, with the most prominent lists suggesting between 3 and 11 basic emotions. These usually include fear, anger, sadness, joy, love, and surprise, all of which can occur simultaneously or in rapid sequence to influence appraisal of and subconscious reactions to events (Ekman, 1992; LeDoux, 1998).

### 1.3 Implications for conservation

Because emotional responses influence one’s appraisal of all concepts, studies that explore people’s emotions could enhance our understanding of conservation. Identifying emotional reactions can explain why some policies are adopted by policymakers, and how people might respond to conservation policies (Nelson, Bruskotter, Vucetich, & Chapron, 2016; Wilson, 2008). In fact, some studies have found that affect and emotions are a better predictor of final decisions, including policy support, than the more common studies that measure the influence of social values (Angie et al., 2011; Charpentier et al., 2016; Slagle, Bruskotter, & Wilson, 2012).

Despite this, there are surprisingly few studies about the interaction of human emotion and conservation. Those that have been published tend to focus on the role of emotions in human–wildlife interactions in natural and zoo environments (Crossley, Collins, Sutton, & Huveneers, 2014; Powell & Bullock, 2014; Sponarski, Vaske, & Bath, 2015; Straka, Miller, & Jacobs, 2020; Wieczorek Hudenko, 2012), and the influence of outreach and education on emotional and behavioral responses (Johansson, Ferreira, Støen, Frank, & Flykt, 2016, Jacobs and Harms, 2014). These studies employed self-report measures of sentiment (positive to negative valence), but did not identify culturally defined basic emotions. While self-report measures are one way to capture emotion data, and valence is one way to operationalize affective responses, they are far from comprehensive.

### 1.4 Analyzing emotions

Natural Language Processing (NLP), originally named Computational Linguistics, is a discipline of computer science that extracts, analyzes, and produces meaningful representations of language (Liddy, 2001). NLP developers have created tools such as predictive text, text-to-speech abilities, and written or audible machine translation capabilities (Hirschberg & Manning, 2015; Liu, 2015). They have also developed analyses to identify basic emotions associated with text or symbols.

Accurately identifying emotions in texts requires an interdisciplinary approach informed by cognitive psychology and linguistics to create a foundation that computer scientists use to build emotional analysis software. Although psychologists have seldom identified emotions through natural language, focusing instead on psychological states of mind, physiological reactions, and theory (Liu, 2015), many recognize that words create and represent the social reality of emotion (Feldman Barrett, 2017).
Only in the past decade have scientists found NLP to be sufficiently developed for robust emotion analyses.

There are various NLP techniques used to identify emotions in text (Jain, Kumar, & Fernandes, 2017). One approach uses unsupervised classification based on an emotion lexicon which is a list of words or symbols and their associated emotions. Supervised classification, on the other hand, refers to the use of training data by computer algorithms to infer patterns in source text and extrapolate future annotation (Jackson, Watts, List, Drabble, & Lindquist, 2020; Liu, 2015). There are numerous emotion lexicons that vary in their coding, types of measurement, and languages, words, and symbols they can be coded for. Tabak and Evram (2016) and Kušen, Cascavilla, Figl, Conti, and Strembeck (2017) compared four commonly used general emotion lexicons and both found that the National Research Council's (NRC) Emotion Lexicon performed the best in correctly classifying emotions as compared to human annotation.

In this study, we share the novel use of a basic emotion analysis of public response to conservation policy. Using a script developed in Python 3.7+ to apply the NRC Emotion Lexicon, we evaluated the most commonly occurring basic emotions in over 17,000 public responses to conservation policies for the endangered Southern Resident orca population. We explore our findings' implications for more effective public communications and consideration of stakeholder concerns.

2 | METHODS

2.1 | Data sources

Public response data were obtained from four sources, all associated with the governor of Washington’s request for public feedback regarding Southern Resident conservation recommendations. The first dataset included public comments submitted through the governor’s website from July 2018 until May 2019 (cleaned N = 3,446). The second included public responses via SurveyMonkey to 16 specific recommendations provided in a first draft of the governor’s Orca Task Force from September to October of 2018 (cleaned N = 11,323). The third were letters and emails to state agency staff and Task Force members that were submitted from July to November of 2018 (cleaned N = 59). The fourth were personalized comments included on a petition submitted to the governor’s office by the nonprofit environmental law organization Earthjustice in October 2018 (cleaned N = 2,287). Survey prompts were bland, unvaried, and not designed to assess emotion. Using the conditional formatting and SEARCH function within Excel, we identified and excluded all responses that were either complete or near complete duplicates, the latter defined as having minor augment to other text entries. We also excluded attachments and additional documents provided by respondents from our analysis.

2.2 | Lexicon

The National Research Council Canada’s (NRC) Emotion Lexicon version 0.92 was developed using Amazon’s Mechanical Turk to crowdsource human annotation of over 14,000 words into categories of positive sentiment, negative sentiment, and eight emotions of joy, trust, fear, surprise, sadness, anticipation, anger, and disgust (Mohammad & Turney, 2013). In the NRC lexicon, words can be associated with multiple emotions or be neutral and assigned to no emotions. The lexicon allows for reliable detection of emotion within text indicated by the presence and frequency of these 14,000 common words and phrases. The use of this lexicon makes it possible to detect the emotional tone expressed in larger data sets than can be managed through manual coding.

2.3 | Program

Using Python 3.7+ and Java 1.8+ we developed a code to operationalize the NRC lexicon with any text data (Nguyen & Noelcke, 2020). The program specifics can be viewed at the repository: http://doi.org/10.5281/zenodo.4009838, which has been made publicly accessible. The program uses Stanford CoreNLP (Manning et al., 2014) as a textual analysis pipeline which parses strings of text and tags them with various syntactic and semantic attributes. It then cross references each individual word in the comment to the lexicon to be associated with the emotions and scored using a binary scale of 1-present or 0-not present for each of the eight emotions. We developed 16 terms as negators (e.g., nor, not, do not) that if found in the string of text negate the proceeding term by inverting the emotion scores. The output of the program is a CSV file that returns the number of times each emotion was evoked per cleaned response.

2.4 | Intercoder reliability and modifications

We validated the internal reliability of the lexicon against our data by comparing the program output to that of a human coder for at least 10 entries from each of the four
datasets, with a total of 75 entries coded. We used a Pearson correlation test in SPSS 25 and found correlations at or above 70% for all emotions, the threshold commonly considered acceptable for reliability (Hayes & Krippendorf, 2007). Specifically, the human coder and the emotion analysis program agreed 70% of the time for anticipation, 73% for joy, 78% for trust, 85% for disgust, 86% for surprise, 89% for sadness, 90% for fear, and 92% for anger.

To achieve these results we iteratively modified the lexicon based on an evaluation of how the most coded emotive words for each emotion were used in context. This process elucidated the need to remove, add, or alter coding for various words, making this general emotion lexicon more specific to our own data and context. For example, the terms “lower”, “snake”, and “force” were all negatively associated words in the lexicon but in our context were used to reference the names of a dam (on the lower Snake River) and the Orca Task Force. We therefore removed these terms from the lexicon. We also added a number of words related to existing words in the lexicon, coding them identically, such as “dead” (deceased), and “please” (plea). Lastly, we altered the emotional coding of “calf” and “daughter”, which are positive emotive words in the lexicon. Because they were commonly used to reference a female orca calf that died in 2018, they were clearly associated with negative sentiment in our data.

2.5 | Analyses

We identified the number of words per comment that were associated with each of the eight emotions. Frequency of emotion for the four datasets was then compared using the independent samples Kruskal–Wallis Test in SPSS 25, exploring if different response elicitations were associated with more or less emotional expression. We then identified the top 10 words for each emotion across datasets. Additionally, we calculated the average number of emotional words per response to identify highly emotive outlier comments, and the ratio of total words to emotion words to consider the emotional “density” of the content. To describe potential patterns in the expression of emotion associated with orca population and orca governance events, we averaged the number of emotional responses per day by emotion and associated these with high-media events.

To explore trends in the most commonly cooccurring emotions, we ran agglomerative hierarchical cluster analyses using the nearest-neighbor (or single-linkage) method with squared Euclidean distance and no distance thresholds for respondents in our data and for existing relationships in the lexicon. Because annotators were able to assign more than one emotion to each word in the development of the lexicon, we wanted to qualitatively compare the hierarchical cluster analysis of coexpressed emotions in our dataset with a hierarchical cluster of the lexicon itself to clarify the extent to which our data deviated from foundational emotive relationships in the English language. The lexicon data matrix held binary data for each of the 14,000 words (in rows) against columns associated with the six emotions. For example, annotators associated the word abolish with the emotion anger but no other emotions. The database thus had a “1” in the cell associated with abolish and anger and a “0” in the cells associated with abolish and all other emotions. Our project database had individual respondents in the rows and their frequency of expressing each emotion in the columns. To create a relevant comparison of emotion cooccurrence, we transformed the responses into binary presence/absence of each emotion rather than full counts.

3 | RESULTS

The frequencies of associated emotions were significantly different between the four datasets: anger (Kruskal–Wallis H test = 408.89, p = .000), anticipation (Kruskal–Wallis H test = 566.50, p = .000), disgust (Kruskal–Wallis H test 612.62, p = .000), fear (Kruskal–Wallis H test = 427.09, p = .000), joy (Kruskal–Wallis H test = 538.10, p = .000), sadness (Kruskal–Wallis H test = 642.73, .000), surprise (Kruskal–Wallis H test = 487.26, p = .000), and trust (Kruskal–Wallis H test = 517.73, p = .000). Post hoc tests found that these differences were true for all pairwise comparisons between datasets, except that the distribution of sadness (test statistic = −12.62, p = 1.000), trust (test statistic = 217.241, p = .262) and surprise (test statistic = −143.68, p = .800) were not significantly different between the Earth Justice dataset and the Draft Comments response dataset.

With our four datasets combined, the relative frequency of emotions was 22% trust, 18% anticipation, 15% fear, 11% joy, 11% sadness, 8% surprise and anger, and 7% disgust (Figure 1). Trust was most associated with words such as save, food, and governor; anticipation with time, immediately, and plan; fear with watching, remove, and endangered; sadness with remove, problem, and death; surprise with wild, good, and death; anger with remove, death, and money; and, lastly, disgust with pollution, creatures, and death.

The letters and emails were both longer (average 433 words per response) and more emotive (average 66 emotive words per response) than any of the other datasets (Table 1). The submissions associated with Earth
Justice were both shorter and less emotive than all other databases. The general responses to the governor’s website survey were longer and more emotive than the responses specifically focused on the draft task force recommendations. At the database scale, however, the emotional density of the three non-Earth Justice datasets were relatively similar, at about 1 emotive word for every 6–7 words.

Public response data were provided to the governor’s office between July 2018 and May 2019, coinciding with the loss of orca individuals and the Orca Task Force recommendations (Figure 2). Three events involving the Southern Resident population occurred during the public responses: (1) in June an orca went missing and was presumed dead, (2) later the same month a newborn calf died shortly after and was carried by the mother, J35, for 17 days, and (3) in September another orca was proclaimed to be emaciated and went missing, presumed dead. These three events and the release of the task force recommendations approximately align with six discernable spikes in the average emotional response for all emotions to submissions on 7/27, 8/24, 10/14, 10/26, 11/1, and 11/23. Emotional spikes were predominantly temporally aligned, though we note spikes for trust, joy, and anticipation later in the month of August surpass the expression of other emotions, and disgust peaked a few days earlier in March of 2019 than other emotions.

Figure 3 gives a visual representation of the coding process, showing the emotions associated with emotive words from the NRC Lexicon. Each of the three examples is a highly emotive comment by an individual respondent. The first quote demonstrates a common message in the data: the respondent connects the health of the orcas to overall environmental goods and services for the surrounding area, and also connects these aspects to personal experiences and memories. In this example, trust and joy are the most expressed emotions, although all eight emotions are associated in the quote. The words food, joy, happiness, good, clean, and pay are associated with the emotion joy. The words food, nation, good,
clean, pay, and real are associated with trust. This example also shows how one word can be associated with more than one emotion, as with the correlation between trust and joy in the words clean and food. The second quote represents another common pattern in comments: people who refer to the governance process frequently expressed anger, surprise, and sadness. All three of these quotes demonstrate how each individual generally...
expressed multiple emotions within the same piece of writing.

Respondents expressed cooccurrence of emotions in two divergent ways than the general patterns of emotion cooccurrence in the English language, as revealed in the NRC lexicon. Specifically, our data (Figure 4a) show (1) a clear division between more positive emotions like joy, trust, and anticipation and the other emotions and (2) a highly nested pattern for the more negative emotions relative to the lexicon (Figure 4b). Most notably, respondents who expressed surprise were more likely to also express fear, anger, sadness, and disgust as opposed to joy, surprise, and trust. That is, words associated with surprise were more frequently found with words that convey negative or unpleasant emotions. Additionally, respondents who expressed joy were likely to express words associated with trust more often than indicated by the lexicon. Respondents who expressed anticipation were more likely to express surprise and disgust than is in the lexicon. And fear and sadness were more frequently cooccurring in our data, as were anger and disgust.

4 | DISCUSSION

4.1 | Understanding the basic emotions associated with orca conservation

We aimed to identify the frequency of basic emotions presented in written responses to orca conservation strategies, the context in which these emotions were being used, if specific emotions were more likely to cooccur in this context, and the extent to which emotional responses correlated to orca-related events.

The most common emotion associated with orca conservation was trust. In defining trust as a basic emotion, Plutchik (1962) described it as reflecting a willingness to pursue or allow particular things. After reviewing the most common words associated with this emotion, and the responses with highest density of words associated with trust, we interpret that respondents have strong faith that if particular actions are taken the orcas can be saved. There is an overall trust that their recovery can be attained. One of the top 10 most frequently coded words for trust was governor. We found this word most commonly used to directly address the WA state governor and to point out the capabilities and power of the position in response to orca decline. The fact that respondents chose to address the governor suggests they have some level of recognition and acceptance of this person’s power to resolve the situation. Conservation organizations could build on this revealed public acceptance of power by developing strategic actions and messaging that establish the governor’s office as leading the efforts to implement orca conservation.

Anticipation and fear were the next most frequent emotions, reflected in the words urgency, immediately, loss, death, die, starvation, harm, and young. These terms were used empathetically to describe strong concern with the health of orca populations and to demand that action be taken now—the time for research and discussion was over. Respondents cited the amount of research that has been gathered over the years, specifically about the impact of dams on salmon resources and ocean pollution, and the minimal action taken to address such research implications. Many comments with fear content focused on the starvation of individual orcas due to a lack of salmon spawning and the inability to reproduce and care for their young. They also expressed concern about the orca aging out of reproductive age and not being able to...
maintain the population. Conservation managers can use this inherent empathy for orcas, and people’s understanding of the issues affecting their health, when highlighting how different strategic options are likely to succeed at helping the orcas thrive.

Joy and sadness, contrasting emotions in Plutchik’s framework, had the same frequency of being expressed within our dataset. Joy was largely associated with creating and sustaining safety for orcas through measures such as ensuring adequate salmon harvest amounts and improving the quality of the Salish Sea. Personalized explanations of why the orca species is of importance to respondents made up another large part of the expression of joy, and was conveyed through words such as beauty, magnificent, precious and majestic. Sadness, anger, and disgust were customarily exhibited when respondents spoke about the perils that orcas face. While all three emotions were present when mentioning the death and suffering of the animals, only sadness was used when speaking about urgency and pleading that something be done before it is too late. References to the situation regarding orca J35 and its calf were also highly mentioned within comments expressing sadness and disgust.

The fact that we identified multiple emotions within each response is common. In fact, clinical experience shows that persistent mixed emotions are more common than a single emotion in most contexts (Plutchik, 1962). Basic emotions can be blended, creating additional emotions (e.g., according to Plutchik’s framework, anticipation and joy combine to form optimism) or representing different levels of arousal (e.g., pensiveness being a less intense feeling compared to sadness, and grief being the strongest experience of sadness). They can also be rapidly sequenced (Ekman, 1992). The persistence of mixed emotions in this conservation context highlights the complexity of the human context to which government needs to respond, and the need to explore the personal and contextual variables influencing the variety of emotions. Although we do not have personal data associated with these over 17,000 public responses, we do know that the more positive words were often in reference to the orcas themselves, whereas the more negatively associated words were in reference to the policy options and processes associated with orca conservation.

Surprise may have been more commonly associated with disgust and anger due to the recoding of the terms mother and child. In the lexicon, these words were associated with anticipation, trust and joy. Based on our analysis of their use in the orca conservation comments, however, they were almost entirely in reference to the J35 event. These comments often mentioned how the respondents could sympathize with how it would feel to lose a child, therefore changing these terms to become associated with surprise and sadness. The fact that the emotional domain of surprise is clearly associated with negative or unpleasant emotions in the orca context, as compared to its general association with positive and pleasant emotions in the English language, suggests that people’s baseline assumption and strong preference is that orca populations and individuals are fine. News items that share negative information about the population, especially information that is easily anthropomorphized, evoke surprise that links to the negative realm of emotions. This has implications for human behavioral responses as we discuss below. Additionally, the frequent cooccurrence of joy and trust shows an emotional connection between people’s positive associations with orcas and their need to accept the agency of the governor and others to resolve their plight. The tight connections between sadness and fear, and anger and fear allude to how respondents are dealing with different sources of distress regarding the situation. The fact that these emotions are cooccurring higher than their baseline correlation in the lexicon shows that events involving orca safety and governance elicit a higher than normal emotional response. Managers of orca conservation should keep in mind the impassioned nature of the situation and recognize the emotionally laden subject carefully. Making statements of fact in emotional contexts, for example, will do little to modify the public’s cognitive and behavioral responses (Sharot, 2017).

4.2 Cognitive and behavioral implications

Because emotions drive how we feel and behave, there are some indications that understanding them could help us understand people’s conservation actions (Angie et al., 2011), but we should be careful to not assume predictive power from emotional assessments (Chapman, Lickel, & Markowitz, 2017). While some studies have found that negative emotions tend to have more standardized reactions than positive emotions, there is substantial variation of behavioral response options across all emotions (Feldman Barrett, 2017). That said, a meta-analytic review of how discrete emotions have been found to influence decision-making noted that angry individuals tend to stereotype targets, use heuristics to make judgments, and show automatic prejudice toward out-group members compared to people presenting sad and neutral emotions (Angie et al., 2011). Sad people engaged in more thoughtful and detail oriented cognitive tasks, and happy individuals were more likely to choose...
safe options than sad individuals. Particularly interesting for conservation, angry individuals were more likely to cite human factors as the cause of negative events, perceive lower levels of past and present risk, and support more punitive policies, while fearful individuals were more likely to cite situational factors as the cause of negative events, perceive higher levels of risk, and prefer more protective policies. And, specifically, anger and sadness had the highest effect on people’s policy choices (Angie et al., 2011). While anger was not particularly high in our dataset, the higher presence of fear and sadness suggests that people would be willing to accept more protective orca conservation strategies, especially after “surprising” events, than when this emotion is not as prevalent.

The few studies on wildlife conservation that have explored emotion have confirmed that affect (measured as valence) toward wolves predicts the acceptability of some types of wolf management actions (Straka et al., 2020). Specifically, affect was predictive of people’s support for no action or education-based action. Support for lethal control was more reliably predicted by domination values than by expressed emotion. Slagle et al. (2012) found that affect, also measured as valence toward wolves, largely influenced people’s beliefs about the outcomes of wolf management, and ultimately their support for wolf management policies. These studies demonstrated that positive or negative assessments of animals are important, but they did not employ analysis of discrete emotional mechanisms for those assessments, or how those assessments could be related to the policymaking process as opposed to the animal itself. Additionally, they relied on stated emotions, which some research suggests is less reliable than revealed emotions as people may mis-categorize or mis-label their own emotions (LeDoux, 2000).

4.3 Advancing conservation social science

Identifying basic emotions in conservation contexts takes conservation social science a step further than it has gone to date. Most affective research in conservation has focused on emotional responses to specific species (Jacobs, 2012), and studies that integrate basic emotions tend to focus on fear. Yet emotions, as core factors in mental processing, are a fundamental part of the entire conservation decision-making process. This recognition is not always represented in conservation narratives (e.g., Shine, 2011). Additionally, most affective research associated with conservation has focused on studies of valence (or sentiment) which informs whether an individual is more likely to “approach” or “avoid” the context (Izard, 2007). The study of discrete emotions adds to this analysis a consideration of how and why people might approach (support) or avoid (reject) conservation actions.

Thus, the goal of assessing emotions in conservation is to inform conservation decision making by taking a full account of the factors influencing creation and acceptance of decisions (Wilson, 2008). One step is identifying the emotional context, as we have done here. But deeper understanding will come from the recognition that individual emotional reactions to conservation policy are based on a combination of historical experiences and current context. Jacobs and Vaske (2019) identify novelty, valence, norms, agency, and goals as the five dimensions through which humans evaluate the emotional relevance of stimuli. In a conservation context, individuals tend to assess policy proposals based on their receptivity to change, moral valuations, subcultural norms, ability to control outcomes and whether or not they further personal goals. This current study, based on a large public comments dataset, does not consider individual respondents’ context to understand the antecedents to their emotional responses. If a conservation agency were interested to better describe the “why” of existing emotions, they would need to support research that measured these potential explanatory variables in addition to the emotional responses.

4.4 Thoughts on methodology

We found that the average amount of emotion portrayed depended on the prompt to which people responded. In our case, the smallest dataset (the letters and emails) had the most emotion per response. These letters and emails were not in response to a specific prompt; rather, individuals responded to the social and political events during the time at their own initiative, often with much longer written reactions. The largest dataset in our research (those responding to the task force strategy draft), however, consisted of individuals who were prompted to respond to 16 proposed orca conservation actions. The format and sponsoring agency from which responses are solicited and gathered may affect emotional responses; depending upon the type of responses managers would like to receive, they should prompt and solicit respondents accordingly. A characteristic of big data is that it is often unstructured or compiled from multiple sources, and NLP provides an automated method for evaluating subtextual emotion irrespective of prompting.

When using emotion analysis on a large scale there is naturally a loss of fine-grained detail and rich
description. The alternative of focusing on only small-n qualitative studies, however, has frequently been identified as not necessarily representative of the large system some managers are tasked to address. Additionally, qualitative data collection and analysis is sometimes avoided due to lack of training by practitioners in conservation agencies and intensive time requirements associated with engaging in thoughtful interviewing. NLP emotion analysis is an additional option that provides generalizable and representative results of the emotions and sentiment harbored by the study population that can subsequently be used to design more in-depth studies that clarify antecedents of emotions through either qualitative interviews, qualitative media or political analyses, or statistical comparisons to other large-scale datasets such as natural resource or public health trends.

5 | CONCLUSION

Perception, cognition, decision making, judgment, and action are all influenced by emotion (Izard, 2007). This includes those cognitions, decisions, and actions relevant to conservation. In this study, we assess discrete emotions associated with over 17,000 written public responses to Southern Resident orca conservation policy considerations. We found that respondents frequently held mixed emotions, most commonly including trust, anticipation and fear. Overall, respondents believed and trusted that Southern Residents could be saved through urgent and extensive actions to procure food and safe environments for the species and that the state government had the power to remedy the situation with high-priority actions and measures. Simultaneously, respondents expressed their anticipation and fear of the situation while mentioning the pressing nature of it, the suffering of the animals, and the need to move past planning to action. We also found that the emotion of surprise was more correlated to negative emotions in our datasets than it is within the lexicon, suggesting that although the health of the Southern Resident population has been decreasing for quite some time, witnessing the continued deaths and hardships of the orcas exacerbates the connection of being surprised with negative emotions. Identifying these discrete emotions has implications for assessing people’s motivations to support, remain neutral, or actively reject conservation policy. It also provides information about how different audiences are inclined to take these stances, though we should be careful to not assume specific individual behavioral predictions as a result of the presence of basic emotions. Adding such knowledge to the repertoire of conservation scientists can only improve our understanding of conservation decision-making.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hailey Kehoe Thommen oversaw the development of the python program, conducted all data analysis, led the manuscript development process, and wrote the methods and results sections. Karin Swarbrick organized the public data for analysis, prepared all images, and substantially edited early version of the writing. Kelly Biedenweg oversaw and funded student time on the project, conceptualized the research question, and wrote the introduction and discussion sections.

ETHICS STATEMENT

Data used for this analysis were publicly available, and thus do not constitute “human subjects” data requiring IRB approval. Even so, we removed all personal identifiers in databases and have only made population-level analyses.

DATA AVAILABILITY STATEMENT

Data are available at: https://kellybiedenweg.weebly.com/peer-reviewed-publications.html.

ORCID

Kelly Biedenweg https://orcid.org/0000-0002-9230-1315

REFERENCES

Angie, A. D., Connelly, S., Waples, E. P., & Kligyte, V. (2011). The influence of discrete emotions on judgement and decision-making: A meta-analytic review. Cognition & Emotion, 25(8), 1393–1422.

Chapman, D. A., Lickel, B., & Markowitz, E. M. (2017). Reassessing emotion in climate change communication. Nature Climate Change, 7(12), 850–852.

Charpentier, C. J., De Neve, J. E., Li, X., Roiser, J. P., & Sharot, T. (2016). Models of affective decision making: How do feelings predict choice? Psychological Science, 27(6), 763–775.

Crossley, R., Collins, C. M., Sutton, S. G., & Huveneers, C. (2014). Public perception and understanding of shark attack mitigation
measures in Australia. Human Dimensions of Wildlife, 19(2), 154–165.
Ekman, P. (1992). An argument for basic emotions. Cognition & Emotion, 6(3–4), 169–200.
Feldman Barrett, L. (2017). How emotions are made. NY, NY: Mariner Books.
Ford, J. K. (2009). Killer whale: Orcinus orca. In Encyclopedia of marine mammals (pp. 650–657). San Diego, CA: Academic Press.
Ford, J. K., Ellis, G. M., & Balcomb, K. C. (1996). Killer whales: The natural history and genealogy of Orcinus orca in British Columbia and Washington. Seattle, WA: UBC press.
Ford, J. K., Ellis, G. M., Olesiuk, P. F., & Balcomb, K. C. (2010). Linking killer whale survival and prey abundance: Food limitation in the oceans’ apex predator? Biology Letters, 6(1), 139–142.
Hayes, A. F., & Krippendorf, K. (2007). Answering the call for a standard reliability measure for coding data. Communication Methods and Measures, 1(1), 77–89.
Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. Science, 349(6245), 261–266.
Izard, C. E. (2007). Basic emotions, natural kinds, emotion schemas, and a new paradigm. Perspectives on Psychological Science, 2(3), 260–280.
Jackson, J. C., Watts, J., List, J. M., Drabble, R., & Lindquist, K. (2020). From text to thought: How analyzing language can advance psychological science. PsyArXiv PrePrints. https://doi.org/10.31234/osf.io/qr4t9.
Jacobs, M. H. (2012). Human emotions toward wildlife. Human Dimensions of Wildlife, 17(1), 1–3. https://doi.org/10.1080/10871209.2012.653674
Jacobs, M. H., & Harms, M. (2014). Influence of interpretation on conservation intentions of whale tourists. Tourism Management, 42, 123–131.
Jackson, M. H., & Vaske, J. J. (2019). Understanding emotions as opportunities for and barriers to coexistence with wildlife. In B. Frank, J. A. Gilkman, & S. Marchini (Eds.), Human-wildlife interactions: Turning conflict into coexistence. Conservation biology (pp. 65–84). Cambridge, UK: Cambridge University Press.
Jain, V. K., Kumar, S., & Fernandes, S. L. (2017). Extraction of emotions from multilingual text using intelligent text processing and computational linguistics. Journal of Computational Science, 21, 316–326.
Johansson, M., Ferreira, I. A., Støen, O. G., Frank, J., & Flykt, A. (2016). Targeting human fear of large carnivores—Many ideas but few known effects. Biological Conservation, 201, 261–269.
Jones, R. (2013). Running into whales: The history of the North Pacific from below the waves. The American Historical Review, 118(2), 349–377.
Kušen, E., Cascavilla, G., Figl, K., Conti, M., & Strembeck, M. (2017). Identifying emotions in social media: Comparison of word-emotion lexicons. Paper presented at the 2017 5th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW) (pp. 132-137). IEEE.
LeDoux, J. (1998). The emotional brain. London: Phoenix Publications.
LeDoux, J. E. (2000). Emotion circuits in the brain. Annual review of neuroscience, 23(1), 155–184.
Liddy, E. D. (2001). Natural language processing. In Encyclopedia of Library and Information Science (2nd ed.). New York: Marcel Decker, Inc.
Liu, B. (2015). Sentiment analysis: Mining opinions, sentiments, and emotions. Cambridge, England: Cambridge University Press. https://doi.org/10.1017/CBO9781139084789.002
Lusseau, D., Bain, D. E., Williams, R., & Smith, J. C. (2009). Vessel traffic disrupts the foraging behavior of southern resident killer whales Orcinus orca. Endangered Species Research, 6(3), 211–221.
Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J. R., Bethard, S., & McClosky, D. (2014). The Stanford CoreNLP natural language processing toolkit. Paper presented at the Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations (pp. 55–60).
Mohammad, S. M., & Turney, P. D. (2013). NRC emotion lexicon. Canada: National Research Council.
Nelson, M. P., Bruskotter, J. T., Vucetich, J. A., & Chapron, G. (2016). Emotions and the ethics of consequence in conservation decisions: Lessons from Cecil the lion. Conservation Letters, 9(4), 302–306.
Nguyen, C. & Noelcke, T. (2020). osu-cass/OrcasAnalysis: Orca Emotion Analysis Public (3.0) [Computer software]. Zenodo. https://doi.org/10.5281/ZENODO.4099838
NMFS (2002). Status review of southern resident killer whales (Orcinus orca) under the endangered species act. NOAA Technical Memorandum NMFS-NWFS-54. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service.
Plutchik, R. (1962). The emotions: Facts, theories and a new model. New York, NY: Random House.
Plutchik, R. (1994). The psychology and biology of emotion. New York City, NY: HarperCollins College Publishers.
Powell, D. M., & Bullock, E. V. (2014). Evaluation of factors affecting emotional responses in zoo visitors and the impact of emotion on conservation mindedness. Anthrozoös, 27(3), 389–405.
Ruby, R. H., & Brown, J. A. (1981). Killer whales: The natural history and genealogy of Orcinus orca in British Columbia and Washington. Seattle, WA: UBC press.
Sharot, T. (2017). The influential mind: What the brain reveals about our power to change others. London, UK: Picador.
Shine, R. (2011). How can we ensure that conservation policies are based on science, not emotion? Pacific Conservation Biology, 17 (1), 6–10.
Slagle, K. M., Bruskotter, J. T., & Wilson, R. S. (2012). The role of affect in public support and opposition to wolf management. Human Dimensions of Wildlife, 17, 44–57. https://doi.org/10.1080/10871209.2012.6353237
Sponsarski, C. C., Vaske, J. J., & Bath, A. J. (2015). The role of cognitions and emotions in human-coyote interactions. Human Dimensions of Wildlife, 20, 238–254. https://doi.org/10.1080/10871209.2015.1010756
Straka, T. M., Miller, K. K., & Jacobs, M. H. (2020). Understanding the acceptability of wolf management actions: Roles of cognition and emotion. Human Dimensions of Wildlife, 25(1), 33–46.
Tabak, F. S., & Evrim, V. (2016). Comparison of emotion lexicons. Paper presented at the 2016 HONET-ICT (pp. 154–158). IEEE. United States. (1973). Endangered Species Act of 1973, 16 U.S.C. § 1531.
WA Exec. Order No. 18-02 (2018). Southern Resident Killer Whale Recovery and Task Force. Retrieved from: https://www.governor.wa.gov/sites/default/files/exe_order/eo_18-02_1.pdf

Wieczorek Hudenko, H. (2012). Exploring the influence of emotion on human decision making in human–wildlife conflict. *Human Dimensions of Wildlife, 17*(1), 16–28.

Wilson, R. S. (2008). Balancing emotion and cognition: A case for decision aiding in conservation efforts. *Conservation Biology, 22*(6), 1452–1460.

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