THESIS

EXPLORING COMPENSATION PROGRAMS AND DEPREDATION REPORTING FOR WOLF-LIVESTOCK CONFLICT ACROSS THE NORTH AMERICAN WEST

Submitted by

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ABSTRACT

EXPLORING COMPENSATION PROGRAMS AND DEPREDATION REPORTING FOR WOLF-LIVESTOCK CONFLICT ACROSS THE NORTH AMERICAN WEST

With the continuing reestablishment of wolves (*Canis lupus*) across the American West, livestock producers will be increasingly exposed to wolf-related conflict such as livestock depredation. The financial implications of wolf conflict can be significant depending on the context of an individual livestock operation. Compensation programs administered by government agencies and occasionally non-government organizations aim to ameliorate some of the financial risks associated with wolves and the loss of livestock; yet the effectiveness of these programs at fostering tolerance and adequately addressing losses is increasingly questioned. Reporting depredation is often required for compensation eligibility, and reports are the primary source of data used by wildlife agencies to address conflict and inform local management. Yet not all producers report depredation or utilize compensation, and we know very little about what factors motivate reporting and compensation use. Additionally, we know very little about producer perspectives on existing compensation programs or whether producers are interested in alternatives. I designed an exploratory survey based on an expanded version of the Theory of Planned Behavior to identify the social-psychological and demographic factors most strongly correlated with compensation use and wolf depredation reporting intentional outcomes. I also utilized a simplified Discrete Choice Question to gauge producer interest in alternatives to traditional compensation programs. My online survey was sent to livestock producers across Arizona, California, Colorado, Idaho, Montana, New Mexico, Washington, Wyoming, and Alberta, Canada (n=165 responses). While 87% of respondents experiencing wolf depredation had reported a depredation in the past, only 69% had utilized compensation. Levels of satisfaction with existing compensation programs were mixed. The most common reasons stated for not applying for compensation included dissatisfaction with the depredation confirmation process (too much validation and/or paperwork), that the amount of compensation available is not enough or not worth the hassle of applying for compensation, and a lack of trust and satisfaction with state government employees and their wolf management decisions. Using Lasso regression, I found that descriptive norms ($p<0.01$), age ($p<0.01$), and past experience with depredation ($p<0.05$) were the strongest predictors of reporting intention. Trust ($p<0.001$), perceived risk ($p<0.05$), descriptive and personal norms ($p\leqq 0.05$), attitudes ($p<0.05$), and state of residence (varied by state) had the strongest relationship with compensation use intention. The overall predictive power of my models was high, suggesting the expanded Theory of Planned Behavior model was effective at predicting both behavioral intentions. The results of my Choice Question suggest that my surveyed population wants access to diverse and adaptive payment and engagement options for wolf depredation. I also found that although these producers are interested in alternatives like Habitat Leases and Cost-Shares for financial and technical assistance with conflict reduction tools, they still want access to traditional compensation for depredation to address local variation in depredation across neighboring operations. Although limited by my sample size, these findings suggest that 1. building interpersonal trust between wildlife agency personnel and livestock producers, 2. reducing wolf-related financial vulnerability by providing compensation for indirect losses and/or undetected wolf depredations in addition to payments for depredation, and 3. building descriptive norms by providing peer-to-peer knowledge sharing opportunities for producers to share with one another may all increase reporting and compensation use intentions among livestock producers, and by extension, may influence behavior.

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1 Introduction

1.1 Background

Carnivore-livestock conflicts are one of the most contentious aspects of large carnivore conservation and management. Livestock depredation can lead to threatened economic interests and human safety, fueled tensions, taxed inter-stakeholder relationships, and the lethal removal of vulnerable wildlife (Nie 2001, Oakleaf et al. 2003, Madden 2004, Fox et al. 2006, Muhly and Dubois et al. 2009, Breck 2011, Scasta et al. 2017, Harris 2020). Through a combination of natural expansion and two reintroduction efforts in the 1990's, wolves *(Canis lupus)* have reestablished across the Western United States (Ripple et al. 2014, Niemiec et al. 2020). The negative impacts of wolves are disproportionately born by livestock producers, often in varied and unequal ways. Wolf-livestock conflict can result in direct economic losses to the producer in the form of depredation (when wolves kill livestock) and indirect losses from predator-induced stress, such as reduced weight gain, reduced reproductive rates, and injuries needing veterinary care (Treves and Karanth 2003, Breck 2004, Ramler et al. 2014, Erickson 2016). In addition, there can be large time, energy, and resource investments required by livestock producers to monitor both wolves and livestock in areas with conflict (e.g., working additional hours, hiring additional employees, changing grazing areas or turn out dates, regular communication with wildlife agency personnel, etc.; Dickman et al. 2011, Hoag et al. 2011, Lee et al. 2017).

To mitigate the negative impacts of wolf depredation on livestock operations, several state and federal agencies (as well as some non-government organizations) offer compensation programs that pay producers for confirmed wolf depredations (Dickman et al. 2011, Lee et al. 2017, Harris 2020, Macon 2020). How these programs are administered and funded varies widely, but most programs offer fair market price for the animal killed (or what the animal would have been worth when sold). Adapted from

Richard Harris' discussion paper on international compensation programs, the most common rationales for these programs cited in the literature include improving: 1. tolerance for predators and fostering coexistence (measured as reduced retaliatory killings of predators, improved producer attitudes toward predators, and improved compliance with conservation protocols) and 2. the economic equity and viability of ranches facing wolf conflicts by distributing the costs of predators over a larger group (Harris 2020). While several studies have explored the utility of compensation programs, the majority have focused on whether compensation improves tolerance for predators and/or fosters coexistence (Montag et al. 2003, Naughton-Treves et al. 2003, Nyhus et al. 2003, Treves et al. 2009, Agarwala et al. 2010, Rigg et al. 2011, Marino et al. 2016,). Few studies have explored the extent to which compensation improves the economic equity and viability of ranching (Muhly and Musiani 2009, Dickman et al. 2011, Anderson et al. 2014, Lee et al. 2017, Harris 2020) and none of these studies evaluated what factors motivate compensation use by the ranching community. Measuring tolerance for wolves is not the same as measuring producer perspectives on compensation, motivators for compensation use, or compensation's ability to improve the viability of ranching in the face of wolf conflict. Compensation programs may be an important element to economic equity within wolf management regardless of whether these programs build tolerance for wolves among producers or foster coexistence. Understanding the motivators and barriers to compensation use, in addition to producer perspectives on compensation's economic and operational utility, will be crucial to the effectiveness of compensation programs at engaging landowners facing growing wolf populations.

Additionally, the link between reporting wildlife conflicts and applying for compensation is under researched. Voluntary reporting is an important source of information for local wildlife managers on the frequency, location, and severity of conflicts with carnivores, and reporting is almost always required for compensation eligibility (Gore et al. 2006, Hristienko and McDonald 2007, Spencer et al. 2007, Wilbur et al. 2018). Yet we know very little about what factors motivate or deter depredation reporting behavior, or how producer experiences with reporting may influence compensation use (and vice versa, where experiences with compensation drive producer reporting behavior, and therefore the accuracy of depredation data used to develop conflict related policy and management protocols). In their study examining the role of compensation programs in Alberta, Canada, Lee et al. (2017) found that the majority of livestock producers experiencing wolf and/or grizzly bear depredation did not report those depredations or apply for compensation for reasons associated with both the reporting and compensation processes. Understanding whether factors related with either behavior are influencing both reporting and compensation use may help wildlife managers and policy makers improve reporting rates and compensation utilization.

1.2 Compensation Programs

Literature exploring producer perspectives on compensation's utility is fairly limited despite the growing number of programs and their increasing expenses (Nyhus et al. 2003 and 2005, Beeland 2008, Dickman et al. 2011, Ravenelle and Nyhus 2017, Harris 2020). From my literature review and work with livestock producers across the West, I identified the following challenges to compensation's perceived utility: 1. detecting carcasses and reporting depredations, 2. the amount of compensation paid, 3. funding sustainability (both actual and perceived), and 4. time and resource investment for reporting and compensation application.

In general, to be eligible for compensation producers must detect a carcass they suspect to be a wolf depredation, report the carcass to the agency running depredation investigations, have the carcass confirmed as wolf caused (probable depredations are often also compensated for), and lastly submit a compensation application (Treves 2002, Harris 2020). Finding carcasses to report can be difficult due to terrain, climate, weather, scavengers, grazing allotment size, and operational capacity (Anderson et al. 2002, Treves et al. 2002, Breck et al. 2011, Scasta et al. 2018). Oakleaf et al. (2003) found that for as many as eight calves killed by wolves, only one calf was detected by a producer. In some programs, a multiplier is used to account for wolf depredations never detected, however, how large a multiplier should be remains hotly debated (Breck et al. 2011, Hoag et al. 2011, Lee et al. 2017). In Wyoming, producers located within a game management area are compensated seven to one for every depredated animal found, reported, and confirmed, but producers operating outside the management area are only compensated 3.5 to one. Most states don't use multipliers, so producers cannot be compensated for wolf depredations they cannot detect or depredation that are too old and/or scavenged to confirm.

Usually, detected and reported depredations must be investigated by personnel from the appointed wildlife agency who will determine whether a wolf confirmation is appropriate (Treves 2002, Harris 2020). The accuracy of confirmations often depends on the condition of the carcass, the skill of the investigator, and confirmation protocols that vary by state, agency, and compensation administration (Naughton-Treves et al. 2003). Seventy-six percent of landowners in Southwest Alberta reported significant dissatisfaction with their depredation program in part due to the burden of proof required to confirm a kill as wolf-caused (Lee et al. 2017).

Funding for most compensation programs in the United States comes from federal and/or state dollars, hunting license revenue, or private groups. Almost all compensation programs for wolf depredation are limited financially, which may occasionally result in producers waiting years for payments, or producers being paid less than fair market value when funding is limited (Muhly et al. 2009, Lee et al. 2017). This can be a frustrating and disheartening process for producers, resulting in a loss of faith in the system (Dickman et al. 2011, Lee et al. 2017, Macon 2020). Additionally, fair market value may underestimate the true financial losses associated with depredation. Fair market value only accounts for the value of the depredated animal as a consumption good (no future economic production), and not their value as a capital good (having future economic production). Cows and heifers are not only a sellable product for their own meat, but also produce meat through calving, which can be especially important if that animal has highly desirable traits or genetics (Anderson et al. 2014). Additionally, fair market value payments only cover the direct loss, ignoring the indirect losses impacting livestock from wolf-induced stress. Although more research is needed (Hebblewhite 2010, Mabille et al. 2016), several studies have found evidence that predator-induced stress results in reduced seasonal weight gain from increased vigilance (decreased time foraging and more time moving), and reduced pregnancy rates (Rashford et al. 2010, Sommers et al. 2010, Steele et al. 2013, Ramler et al. 2014, Scasta et al. 2018, Valerio et al. 2018 and 2021, Widman and Elofsson 2018). Ramler et al. (2014) found that the economic costs resulting from indirect losses exceeded those of direct losses/depredations in herds with at least one confirmed wolf depredation. At the time of writing, I only found one compensation program in the United States that provides payment for indirect losses (Washington state), but this program is heavily underutilized by producers despite high levels of depredation (personal communication with Washington Department of Fish and Wildlife staff, 2021).

Finally, compensation eligibility can be contingent on producers first implementing conflict reduction tools like fencing/fladry, range riding, or carcass removal, or programs may require applicants allow hunting on their property (WGFD, WDFW). Although conflict reduction tools are sometimes subsidized by agencies and/or conservation organizations to encourage their use, often the resources, maintenance, monitoring, and technical assistance are not covered. Even without this contingency, several studies on producer perspectives found that producers find the reporting and compensation application processes time consuming, resource intensive, and/or not worth the available compensation (Montag et al. 2003, Sommers et al. 2010, Lee et al. 2017, Scasta et al. 2018). Although informative, these studies on producer perspectives would be strengthened by quantitatively evaluating what additional social-psychological and demographic factors drive depredation reporting and compensation use behaviors. My study addressed this research gap by using a social-psychological model to predict behavioral intentions related to wolf depredation reporting and compensation use.

1.3 The Theory of Planned Behavior

The Theory of Planned Behavior (TPB – Ajzen 1991, Fishbein and Ajzen 2011) is a social-psychology model stating that behavioral intentions are the strongest driver of behavior, and these intentions are driven by the three following social-psychological constructs: attitudes, injunctive norms, and perceived behavioral control. For example, if we take depredation reporting to be the behavior of interest, the attitude construct may describe whether an individual finds reporting favorable or unfavorable (Niemiec et al. 2013). Injunctive norms might describe whether an individual believes they are expected to report depredation by others they consider relevant such as neighboring producers, the agricultural community, or friends and family, and perceived behavioral control might describe whether an individual believes they are able to report depredation (e.g., do they know who to call – Nigbur et al. 2010). By modeling behavioral intention instead of behavior, the perspectives of livestock producers who have yet to experience depredation can be included, which are also relevant to future policy and wolf management.

The Theory of Planned Behavior is widely accepted as strongly predictive of behavior, including behaviors related to agriculture, wildlife management, and conservation (Lynne et al. 1995, Armitage and Conner 2001, Manfredo 2008, Nigbur et al. 2010, Willcox et al. 2012, Klöckner 2013, Borges et al. 2014, Van Eeden et al. 2020). Several studies have found strong relationships between attitudes about wildlife management decisions and reporting behavior (Rudolph and Riley 2014, Wilbur et al. 2020), and both qualitative and quantitative studies have found that norms motivate a variety of behaviors related to agriculture and natural resources, including the adoption of new cattle management techniques (Willcox et al. 2012, Borges et al. 2014), invasive species management, private lands conservation, and more (Niemiec et al. 2020). Borges et al. (2014) and Lynne et al. (1995) both found that perceived behavioral control influenced whether cattle producers adopted new management techniques and technologies.

Since its inception, the TPB has been expanded to improve its predictive power. One such modification has been the addition of *personal,* and *descriptive* norms to the *injunctive* norm construct (Cialdini, Kallgren, and Reno 1991, Manfredo 2016, Niemiec et al. 2020). Cialdini, Kallgren, and Reno (1991) describe *injunctive* norms as "...a socially shared rule of conduct … tied to a sanctioning group", whereas *descriptive* norms are "...the visible behavior of others tied to a location". In contrast, *personal* norms are the expectations an individual holds of themselves to carry out certain behaviors (Niemiec et al. 2020). Although subtle, the difference between self-imposed expectation, community-imposed expectation, and mirroring the behaviors of others can have differing influence on behaviors and intentions. For example, in their meta-analysis on conservation behaviors, Niemiec et al. (2020) found descriptive and personal norms to be more significantly associated with behavioral intentions than injunctive norms. Rivis and Sheeran (2003) found that descriptive norms explain an additional 5% of variance when added to TPB variables (Rivis and Sheeran 2003, Norman et al. 2005). Norms are also directly linked to identity formation through shared values (Abrams and Hogg 1990, Van Eeden 2020), an important characteristic of wolf-livestock conflicts in the American West (Manfredo et al. 2016). To improve the predictive power of my models within the context of wolf depredation and compensation, I expanded the traditional Theory of Planned Behavior to include *injunctive, descriptive,* and *personal* norms metrics in additional to the traditional *injunctive* norm metric.

Some expansions to the traditional TPB have included the addition of new constructs all together. For example, several studies have found that personal experience with wildlife influences future behavior related to wildlife conflict, primarily through influence on the formation of attitudes and perceptions of risk (Gore et al. 2006, Lobb et al. 2007, Krester et al. 2009, Wilbur et al. 2018, Van Eeden et al. 2020). Risk beliefs are reliable predictors of normative beliefs, behavioral beliefs, and behavior itself (Slovic 1987, Slovic and Peters 2006, Lobb et al. 2007, Fishbein & Ajzen 2010, Dohmen et al. 2011, Carter et al. 2020, Van Eeden et al. 2020). Risk perception has shown to be a better predictor of behavior than technical assessments of risk, since an individual may justify a behavior they perceive to be high risk if they perceive the benefit(s) of that behavior to be worth the risk (Bruskotter and Wilson 2014). Specifically, perceived risk *probability* and *severity* may influence behavior related to wildlife conflict, as these perceptions capture both emotional and cognitive responses to the threat (Slovic 1987, Howe et al. 2010, Hayman et al. 2012, Sponarski et al. 2018, Wilbur et al. 2018, Van Eeden et al. 2020). In their study, Wilbur et al. (2018) found that Colorado residents who reported having a negative experience with black bears were more likely to report a black bear conflict. Both Krester et al. (2009) and Wilbur et al. (2018) found that bear conflicts associated with property damage or human safety had a larger influence on reporting behavior than incidents with less severe perceived risk (e.g., seeing a bear). To develop my Theory of Planned Behavior model for compensation use and reporting behaviors, I expanded the traditional TPB model to include the following perceived risk metrics: *past experience* with the risk (risk of experiencing wolf depredation), *perceived severity* of the risk event (financial vulnerability to depredation), and *perceived probability* of the risk (level of worry about potential wolf depredation).

Another expansion to the traditional TPB model has been beliefs about the utility of a behavior. This expansion is especially common in studies examining factors driving adoption of new techniques, programs, tools, protocols, etc. (Ajzen 2015, Borges et al. 2015, Lute et al. 2018). Beliefs about the utility of a behavior are distinct from attitudes about that behavior (although related). One may find a behavior unfavorable for reasons outside the behavior's utility, but beliefs about utility may influence overall attitudes (e.g., a producer may perceive depredation compensation to be useful for covering the operational costs associated with wolf conflict, but find the process of applying for compensation onerous, and therefore somewhat unfavorable despite the perceived utility – Conner and Armitage 1998). This distinction may be important for evaluating the specifics of where the reporting and compensation processes can be improved. For my models, I expanded the traditional TPB to include a belief metric for the *utility* of compensation and the *utility* of depredation reporting.

Trust has been identified as a significant driver of behaviors related to natural resources and agriculture, as well as a key driver of successful collaborative stakeholder engagement processes between landowners, livestock producers, hunters, and wildlife management agencies (Davenport et al. 2007, Coleman and Stern 2018, Lute et al. 2018, Dietsch et al. 2021). In the social-psychological literature, trust is defined as an acceptance of vulnerability based on the belief in the goodness of others' intentions and behaviors (Rousseau 1998). Social trust within the context of government requires a willingness to rely on the institutions creating and implementing policies and management (Earle and Cvetkovich 1995, Davenport et al. 2007) and may be based on a perception of shared intentions or values (Siegrist et al. 2003). In their overview of the trust construct in the context of natural resources, Davenport et al. (2007) identify two key assumptions associated with trust: 1. trust requires some degree of dependence by the trustee on the trusted, and 2. trust involves specific expectations. Similar to norms and perceptions of risk, different types of trust may have different influence on behavior. For example, trust in agency personnel (interpersonal trust) may influence reporting behavior differently than trust in the agency itself, outcomes of management decisions, or their required processes (Davenport et al. 2007). From management and community perspectives, understanding where trust can be improved (be it through boots-on-the-ground personnel, or management decisions and processes) may be extremely important. Both a lack of trust in management authorities/personnel (Goudriaan et al. 2004) and a lack of trust in management decisions and processes (Rudolph and Riley 2014, Wilbur et al. 2018) have shown influence on reporting behavior specifically. To capture the complexity of trust as a metric, I further expanded the traditional TPB model by including questions about trust in *state* and *federal* agencies, *environmental groups*, and the *depredation confirmation process* (Davenport et al. 2007).

Demographic factors are commonly used in studies examining human behavior and wildlife, although at varying degrees of predictive power (Hayman et al. 2014). Both Hayman et. al. (2012) and Wilbur et al. (2018) found that older residents were more likely to report encounters and conflict with wildlife, and Wilbur et al. (2018) found the women report more often. Within this study, I wanted to specifically examine *age, gender, state of residence, number and type of livestock owned and/or grazed*, and whether respondents graze on *public and/or private lands*. The number of livestock may influence the perceived severity of a depredation event on the economics of an individual operation, and therefore the intention to report or apply for compensation. Additionally, whether livestock are grazed on public or private lands, the type of livestock, and state of residence (including state specific policies, management, and compensation programs) can influence livestock risk to wolf depredation, the amount of compensation available to the landowner, and the likelihood of depredation detection (Oakleaf et al. 2003, Hanley et al. 2018, Clark et al. 2020), all of which may influence behavioral intentions.

As part of my exploratory analysis, it was important to distinguish if factors related to the compensation application process (e.g., not receiving compensation on time, compensation amount being too low, or finding the process too onerous) were influencing future reporting intention and vice versa (e.g., is a producer unlikely to report in the future because of a negative experience with compensation, or unlikely to apply for compensation in the future because they had a negative experience reporting depredations in the past). The psychology literature generally recommends against including predictor variables not directly associated with the behavior being modeled (Wicker 1969, Eagly and Chaiken 1993, Wicker 1969, Hayman et al. 2014). However, most compensation programs require depredations be reported to, and confirmed by the required personnel, making reporting and compensation behaviors intrinsically linked. To explore this potential relationship, I used my expanded TPB model to create four behavioral intention models – two where only TPB factors associated with the modeled behavior were included called specific models, and two where TPB factors from the other behavior were also included called mixed models (see Figure 1.1).

1.4 Research Questions

My research questions were: 1. *Which social-psychological variables (attitudes, beliefs, norms, perceived risk, trust) and/or demographic variables drive wolf depredation reporting intention?* 2. *Which social-psychological variables (attitudes, beliefs, norms, perceived risk, trust) and/or demographic variables drive wolf compensation use intention?* 3. *Why do producers who experience wolf depredation choose to report (and choose to not report) depredation?* And 4. *Why do producers who experience wolf depredation choose to not use compensation?* I will answer questions one and two using my four expanded TPB models, and questions three and four using three open-ended survey questions yielding qualitative responses. Using thematic content analysis (Marshall and Rossman 1998), I will identify the most common responses to the following qualitative questions: 1. "Why did you choose to report the wolf depredation?", 2. "Why did you choose not to report the wolf depredation?", and 3. "Why did you choose to not apply for depredation compensation?". By using inductive, qualitative methods in addition to quantitative, I will gain detail on producer perspectives quantitative methods alone cannot provide, as well as the opportunity to receive responses I did not anticipate through my focus groups and interviews (Davenport et al. 2007).

Reporting Specific Model:

TPB Reporting metrics + Perceived Risk metrics + Trust metrics + Demographics = Future Reporting Intention

Reporting Mixed Model:

TPB Reporting metrics + **TPB Compensation metrics** + Perceived Risk metrics + Trust metrics + Demographics = Future Reporting Intention

Compensation Specific Model:

TPB Compensation metrics + Perceived Risk metrics + Trust metrics + Demographics = Future Compensation Intention

Compensation Mixed Model:

TPB Compensation metrics + **TPB Reporting metrics** + Perceived Risk metrics + Trust metrics + Demographics = Future Compensation Intention

Figure 1.1 *Expanded Theory of Planned Behavior models (TPB models) for the socioecological system of wolf-livestock depredation, depredation reporting, and compensation use. Specific Models contain only TPB factors related to the behavior being modeled, and Mixed Models contain TPB factors related to both compensation and reporting processes.*

2. Methods

2.1 Study Area

Western states with confirmed wolf populations include Washington, Oregon, California, Idaho, Montana, Wyoming, Colorado, Arizona, and New Mexico. Depending on state-specific political leanings, livestock conflict history, and wolf status, compensation programs vary widely from state-to-state in their funding, administration, and associated reporting protocols (see Table 1.1 for state-specific compensation program summaries). To successfully capture the diversity of experiences with reporting wolf depredation and compensation use, I targeted livestock producers in all nine mainland western states with active wolf populations and Alberta, Canada. Alberta province is part of the Northern Rocky Mountain Range and shares a very similar socioecological system of wolf-livestock conflict to the western United States, including similar compensation programs (Lee et al. 2017, Morehouse et al. 2017 and 2020, Macon 2020).

2.2 Survey Design and Implementation

To inform the development of survey questions, our team facilitated twelve virtual focus groups and five unstructured interviews with livestock producers in Wyoming, Montana, New Mexico, Arizona, Oregon, and California from June through October 2020 (Weiss 1995). These sessions helped me adapt the constructs identified from the theory and literature described above to the specific context of compensation and depredation reporting (Table 1.2). Livestock producers, wildlife managers, researchers, and NGO staff then reviewed a draft of the survey after approval by the Colorado State University Institutional Review Board (protocol #20-10064H). I launched the survey December 2020 via Qualtrics (Qualtrics, Provo, UT), a licensed online survey platform (Couper 2001, Chang and Krosnick 2009, Lowry et al. 2016).

Table 1.1 *Summary of State and Province-Specific Compensation Programs for wolf depredation. Adapted from Harris' 2020 report "Literature Review of Livestock Compensation Programs: Considering Ways to Assist Livestock Producers with Grizzly Bear Conservation Efforts in Montana".*

Location:	**Value paid for confirmed losses:** FMV = Fair Market Value	**Payment for probable:**	**Payment for undetected and/or multiplier used:**	**Prevention measures required:**	**Payment for indirect losses:**	**Funding:**
Alberta	FMV	Yes (0.5 FMV if within 90 days of detection and 10km of a confirmed depredation)	No	No	Yes (veterinary expenses for injuries only)	48% Federal 52% Hunters

Arizona/New Mexico	Calf = $750 Yearling = $1K Cow = $1.2K Bull = $2K	Yes (50% confirmed when available)	No	N/A	Yes (injuries only)	100% Federal
California	No	No	No	No	No	None
Colorado	In Process	NA	NA	NA	NA	NA
Idaho	FMV	Yes (FMV when available)	Yes (case-by-case)	Yes (50% match)	Yes (injuries only)	100% Federal
Montana	FMV	Yes (FMV when available)	No	No	Yes (injuries only when funds available)	10% Federal 85% State 5% Private
Oregon	FMV	Yes (FMV when available)	Case-by-case	Yes	Yes (injuries only)	100% Federal
Washington	FMV if less than 100-acre allotment/pasture 2*FMV if larger	Yes (50% confirmed)	Yes (via multiplier)	Yes	Yes (injuries, and a separate application for indirect losses-reductions in weight gain and/or reproductive rates)	100% Federal
Wyoming	7*FMV if near Yellowstone, otherwise FMV	NA	Yes (via multiplier)	No	Yes (injuries only)	100% Hunters

Table 1.2 *Survey constructs and indicators predicting livestock producer reporting intention and compensation use intention for wolf depredation. I organized survey questions using an expanded version of the Theory of Planned Behavior Model and demographic factors.*

Predictor Variable:	Survey Indicator:
TPB Reporting:	
Attitude	*Would you say your general attitude towards reporting wolf depredations to the required personnel is positive, negative, or neutral?
Perceived Behavioral Control	*I know who to call to report wolf depredations. *Detecting carcasses depredated by wolves is time consuming. *Having carcasses confirmed by the required personnel as wolf depredations is time consuming
Norms:	

Injunctive	*My neighbors and/or community would approve of me reporting wolf depredations to the required personnel.
Descriptive	*What percentage of your neighbors and/or community that experience, (or might experience) wolf depredations do you think report, (or would report) those depredation(s)?
Personal	*Reporting is important for maintaining an accurate record of wolf depredation.
TPB Compensation:	
Attitude	*Would you say your general attitude towards compensation for wolf depredations is positive, negative, or neutral?
Perceived Behavioral Control	*The process of applying for wolf depredation compensation is difficult.
	*The process of applying for wolf depredation compensation is time consuming.
Norms:	
Injunctive	*My neighbors and/or community would approve of me applying for wolf depredation compensation.
Descriptive	*What percentage of your neighbors and/or community that experience, (or might experience) wolf depredations do you think apply, (or would apply) for compensation for those depredation(s)?
Beliefs About Usefulness	*The amount of compensation available to me for wolf depredations is representative of my actual losses.
	*Reporting wolf depredation helps wildlife management agencies identify depredation wolves.
Trust:	
About the process	*I trust the personnel investigating a wolf depredation to investigate fairly.
With the Federal government	*I don't want the federal government involved in my operations.
With the State government	*I don't want the state government involved in my operations.
With environmental groups	*I don't want environmental groups involved in my operations.
Perceived Risk:	
Past experience	*Have you ever experienced wolf depredation?
Risk potential	*Typically, how worried are you about wolf depredations on your livestock?
Risk severity	*Without compensation for wolf depredations, my business would be financially vulnerable.
Demographics:	
Location	*What state do you live in?
Age	*What is your age?
Gender	*What is your gender?
Type of livestock	*Please select the type of livestock you raise and/or manage.
Number of head	*Roughly how many head (of any age and sex class) do you manage in a typical year?
Type of land grazed	*On what lands do you typically graze livestock?

I structured the survey based on a modified mixed-methods version of the Tailored Design Method (Dillman et al. 2014). The survey contained five sections: 1. questions about operational characteristics, 2. questions about the reporting process and reporting intention, 3. questions about the compensation process and compensation intention, 4. questions about an ideal compensation program (see

Chapter 2), and 5. demographic questions. For attitudes, I asked respondents if they would describe their general attitude toward the behavior as positive, negative, or neutral (reporting and compensation use respectively). Perceived behavioral control questions varied slightly between the two behaviors. For reporting, I wanted to know whether respondents knew who to call to report a depredation, and their perceptions regarding the difficulty of detecting depredations and having them confirmed. For compensation, I was interested in whether respondents found the application process difficult and/or time consuming. To measure utility beliefs about reporting, I chose to ask if respondents agreed that reporting helps identify depredating wolves, as this is often the first step to management action from wildlife agencies. I measured compensation's utility based on the extent to which respondents believed the amount of compensation available to them covered their actual losses to wolves (i.e., are compensation payments enough). Since personal norms reflect an individuals' sense of personal responsibility to engage in a behavior, I chose to ask a personal norm question related to reporting only, as compensation use has almost exclusively operational/individual scale benefits.

For the personal norm, I chose to ask respondents whether they agreed that reporting helps to keep an accurate record of wolf depredation. Injunctive norms questions asked respondents if they agreed that their neighbors and/or community would support them engaging in reporting or compensation use, and descriptive norms questions asked what percentage of their neighbors and/or community respondents believed were already engaging (or would engage) in either behavior. Dependent variables (1. intention to report depredation, and 2. intention to apply for compensation) were presented on a five-point Likert scale ranging from 'extremely likely' to 'extremely unlikely' (Joshi et al. 2015, Wilbur et al. 2018, Niemiec et al. 2020). Aside from eight categorical questions, I asked the majority of Theory of Planned Behavior questions on a continuous seven-point Likert scale ranging from 'strongly agree' to 'strongly disagree' (see Appendix for details).

I used purposive sampling via snowballing to distribute the survey (Teddlie and Yu 2007). Western Landowners Alliance, my partner for this study, attracts members with diverse perspectives on wolf depredation and compensation, which we confirmed through our focus group sessions and unstructured interviews with the Alliance's members. Our team emailed an anonymous link of our survey to all Western Landowners Alliance's members, more than 200, followed by emails to state and county-level Cattlemen's, Wool, and Beef Growers' Associations, State and Tribal Farm Bureaus, Extension agents from western universities, and wildlife agency personnel to try and encompass a diversity of perspectives (Dillman et al. 2014). After completing the survey, participants were encouraged to share the survey link with other livestock producers west-wide (Etikan et al. 2016). Our team sent two reminder emails in January and March, then closed the survey in May 2021 with a total of *n=165* responses. Due to the prioritization of anonymity, I did not track how many producers received the survey regardless of whether they took the survey.

2.3 Analysis

I analyzed my three qualitative responses not included in the regressions using inductive thematic analysis (Marshall and Rossman 1998, Braun and Clark 2006, Niemiec et al. 2020). Inductive thematic analysis is a qualitative data analysis technique where themes are derived from the data themselves as opposed to being predetermined and categorized after data collection (Marshall and Rossman 1998). For these questions, I categorized and coded distinct responses until saturation of categories was met, and response frequencies achieved (Niemiec et al. 2020 – see Appendix for details). For example, the response "We are required to report depredation as part of our compensation program" was coded as 'To be able to apply for compensation'.

Prior to regression analyses, I removed survey responses with thirty percent or more questions unanswered, and/or responses without a response to the modeled dependent variable (reporting intention and compensation use intention respectively – Wu et al. 2009). This resulted in *n=130* responses for the specific reporting model, *n=127* for the mixed reporting model, and *n=128* responses for both compensation models. I first tested for correlation among continuous predictor variables across all four models (Vaske 2019). I found correlations of (r = 0.7) or higher for only two variable pairs: 1. between the reporting and compensation *descriptive norm* variables (r = 0.78), and 2. between the compensation related *perceived behavioral control* variables (r = 0.75 – see Table 1.2). I chose to keep both the reporting and compensation *descriptive norms* since they addressed separate behaviors. I combined the *perceived behavioral control* variables into one variable using the mean of responses to both questions for each survey respondent (Wu et al. 2009). Finally, I replaced any remaining missing values across individual question responses with the mean of the total sample (Wu et al. 2009).

I ran two Lasso regressions for each behavior – one for the specific model and one for the mixed model – four total regressions. Lasso regression (Least Absolute Shrinkage Selector Operator) is a regularization method for variable selection in linear modeling that uses cross-validation to determine both the number of predictors and the appropriate shrinkage (Tibshirani 1996, McNeish 2015, SINGH 2021). This method reduces model overfit and makes Lasso regression especially suitable for models with high collinearity between variables and/or large numbers of predictor variables compared to sample size (Meier et al. 2008). By using Lasso, I was able to identify which variables had the most influence on behavioral intention from my large list of 27 potential predictors and relatively small sample size of *n=127-130* depending on the model. I ran the lasso regressions using the *glmnet* package in *R* (v4. 1-1; Friedman et al., 2010). Finally, I ran Ordinary Least Squares regressions on the Lasso-selected variables for each model to obtain interpretable p-values, adjusted estimates, and confidence intervals (Tibshirani 1996, McNeish 2015).

3 Results

3.1 Description of the Sample

Of the total respondents *(n=130),* 72% identified themselves as male, and 28% female. Seventy-three percent of respondents reported to be 50 years of age or older, with most producers reporting to be between the ages of 50 and 69 (53%). Seventy-five percent of all respondents raise or manage cattle, 14%

sheep, and 12% goats and/or other (livestock types not mutually exclusive). The most common operation size was 500 head or less (57%) followed by 500 to 1,000 head (21%), 1,000 to 3,000 head (12%) and 3,000 head or more (10%). Fifty-seven percent of producers reported operating on private lands, 37% on public, and 6% on state or tribal lands (fifty-nine percent of producers operate on both private and public lands). Of the nine states and one province targeted for this survey, 28% of responses came from Montana, followed by California (15%), Wyoming (14%), Colorado (14%), New Mexico (9%), Oregon (6%), Idaho (4%), Alberta (4%), and Arizona (3%). I received zero usable responses from Washington State. Of total respondents, 44% had experienced at least one wolf depredation in the past, 50% had not, and 6% were unsure.

3.2 Findings on Reporting

Of the total respondents, 81% stated they would be likely or extremely likely to report a wolf depredation in the future (future reporting intention). Fifty-one percent of respondents had a positive, or extremely positive general attitude toward the reporting process. Sixty-seven percent of respondents either agreed or strongly agreed (agreed from here on out) that detecting carcasses was difficult, and 76% agreed that having depredations confirmed was difficult (perceived behavioral control). Thirteen percent of all respondents were unsure who to report to (perceived behavioral control), which, although high, makes logical sense with the inclusion of Colorado and California states that do not currently have compensation programs for wolf depredation. Sixty-six percent of respondents agreed that reporting was useful for identifying depredation wolves (beliefs about usefulness). Results for the three reporting-related norms were as follows: seventy-two percent agreed their neighbors and/or community would support them reporting a depredation (injunctive norm), 76% believed 50-100% of their neighbors and/or community were reporting (or would report) wolf depredation, and 79% agreed that reporting is important for maintaining an accurate record of wolf depredation.

Of the respondents who had experienced depredation, 87% had reported at least one wolf depredation. These rates were slightly higher than findings from other studies looking at livestock depredation specifically (Muhly and Musiani 2009, Lee et al. 2017). Using thematic analysis, six distinct themes motivating reporting were identified. The most common reasons stated for reporting were to be eligible for compensation, to have wolves removed and/or management taken, to verify the cause of livestock death, and to maintain an accurate record of wolf conflict.

Of the respondents who had reported a depredation before, 79% stated their general attitude toward reporting was positive or extremely positive. Of these producers with reporting experience, 23% had chosen to not report a depredation at some time. Using thematic analysis, six distinct themes motivating a producer not to report were identified. The most common reasons stated for not reporting included a lack of trust regarding the depredation confirmation process and whether investigators were making fair confirmations, discomfort with government oversight and regulation, and that the time investment (carcass detection and confirmation) was not worth the available compensation.

In general, those with reporting experience believed the reporting process to be more time consuming compared to those who had never reported a depredation (perceived behavioral control for detection and confirmation), and those with experience believed reporting to be slightly more useful (beliefs about usefulness). Trust in the accuracy of depredation confirmations was significantly higher among those who had reported than those who hadn’t (73% and 44% respectively), and those who had reported a depredation were 13% more likely to intend to report future depredation than those who hadn't. All three reporting related norms were higher among those with reporting experience than those without it (90% agree for injunctive, 92% for descriptive, and 83% for personal).

3.3 Findings on Compensation

Of the total respondents, 80% stated they would be likely or extremely likely to report a wolf depredation in the future (future compensation use intention). Forty-five percent of respondents had a positive, or extremely positive general attitude toward being compensated for wolf depredation. Twenty-nine percent of respondents agreed that applying for compensation was difficult, and 42% agreed that it was time consuming (perceived behavioral control). Eighty-eight percent of total respondents believed the compensation available to them was not representative of their actual losses to wolves (beliefs about usefulness). Results for the two compensation-related norms were as follows: sixty-five percent agreed their neighbors and/or community would support them using compensation (injunctive norm) and 67% believed 50-100% of their neighbors and/community were using compensation (or would use compensation) for wolf depredation.

Of the producers who had experienced wolf depredation, 69% had applied for compensation at least once. Sixty-five percent of compensation users stated to have a positive or extremely positive general attitude toward being compensated, although satisfaction with current compensation programs was extremely mixed (see Figure 1.2). Seventy-four percent of producers who had applied for compensation believed the compensation available to them was not representative of their actual losses to wolves (belief about usefulness). Using thematic analysis, nine distinct themes motivating producers to not use compensation were identified. The most common reasons stated for not applying for compensation included dissatisfaction with the depredation confirmation process (too much validation and/or paperwork), that the amount of compensation available is not enough or not worth the hassle of applying for compensation, and a lack of trust and satisfaction with state government employees and their wolf management decisions (see Appendix for details). Compared to the total surveyed population, fewer respondents with compensation experience agreed that the application process was difficult or time consuming (26% and 18% respectively – perceived behavioral control). Both injunctive and descriptive norms related to compensation were higher among those with compensation experience than without

(82% for both norms). Previous compensation users were 18% more likely to intend to use compensation in the future than the total surveyed population.

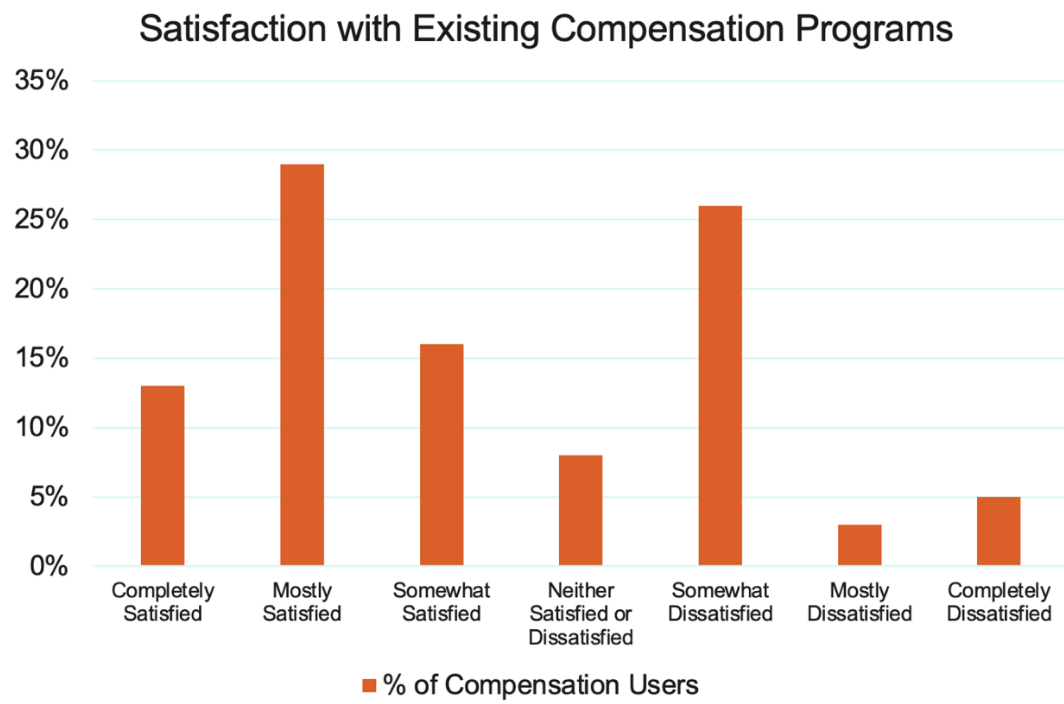

Figure 1.2 *Self-reported satisfaction with current compensation programs among participants who have applied for wolf depredation compensation at least once.*

3.4 Trust and Perceived Risk

Trust in federal and state agencies, and trust in environmental groups (the trust construct for agencies/groups) was extremely similar among those with reporting experience, those who had applied for compensation before, and the total respondent population. About 37% agreed they did not want the federal government involved in their operations, about 31% did not want the state government involved, and about 61% did not want environmental groups involved. Perceived risk *probability* was higher among those with reporting experience than the total surveyed population (75% and 59% respectively), but perceived risk *severity* slightly lower among those with reporting experience (25% and 35%

respectively). Perceived risk *probability* and *severity* were almost identical among those with reporting experience and those with compensation use experience, which makes logical sense as most compensation users would have been required to report depredations to be eligible for compensation.

3.5 Comparing Models

The adjusted R-squared values for the four TPB models were as follows: mixed reporting model – R-squared = 0.38 with p-value <0.001, specific reporting model – R-squared = 0.37 with p-value <0.001, mixed compensation model – R-squared = 0.45 with p-value <0.001, and specific compensation model – R-squared = 0.42 with p-value <0.001. These R-squared values were similar and considered high, suggesting both my specific and mixed models predicted reporting and compensation use behavioral intentions well (Table 1.3). Lasso-selected predictors varied minimally between the simple and mixed reporting models (see Appendix for model-specific Lasso-selected predictors). The Lasso regression identified one additional potential predictor related to compensation use in the mixed reporting model, but compensation related predictors were not identified as significant by the Ordinary Least Squares regression in either reporting model (Table 1.3). Lasso-selected predictors were less similar between the mixed and specific compensation models, notably several reporting related variables were selected in the mixed model. However, only one reporting-related variable was selected by the Ordinary Least Squares regression as statistically significant in the mixed model: the personal norm metric, "Reporting wolf depredations helps wildlife management agencies identify depredating wolves" (p = 0.05).

3.6 Significant Predictors of Reporting Intention

Descriptive norms, age, and past experience with depredation were the strongest predictors of reporting intention within my surveyed population. The higher the percentage of neighbors and/or community members a respondent believed were already reporting depredation (or would report if depredation occurred – my descriptive norm), the more likely their intention to report in the future (p<0.01). The older a respondent, the more likely their intention to report (p<0.01). Past experience with wolf depredation decreased the likelihood of reporting intention (p<0.05 – see Table 1.3). None of the trust metrics or attitude metrics were significant in either reporting model.

Table 1.3 *Selected independent variables from the Ordinary Least Squares regressions predicting: 1. reporting intention and 2. compensation use intention from both specific and mixed models. Ordinary Least Squares regressions were run on the variables selected from the Lasso regressions. Listed variables were selected as statistically significant by Ordinary Least Squares.*

Reporting Mixed Model	**Model Adjusted R-squared: 0.38** **Model P-value <0.001**
More Likely:	**Less Likely:**
Descriptive norm (p<0.01)	Past experience with risk (p<0.05)
Age (p<0.01)	

Reporting Specific Model	**Model Adjusted R-squared: 0.37** **Model P-value <0.001**
More Likely:	**Less Likely:**
Descriptive norm (p<0.01)	Past experience with risk (p<0.05)
Age (p<0.01)	

Compensation Mixed Model	**Model Adjusted R-squared: 0.45** **Model P-value <0.001**
More Likely:	**Less Likely:**

Trust in State agency ($p<0.01$)	Age ($p<0.05$)
Descriptive norm ($p<0.01$)	
Perceived risk severity ($p<0.01$)	
Colorado resident ($p<0.01$)	
New Mexico resident ($p<0.05$)	
Personal norm** **(*p*=0.05)	
Attitude ($p<0.05$)	
Montana resident ($p<0.05$)	

Compensation Specific Model	**Model Adjusted R-squared: 0.42** **Model P-value <0.001**
More Likely:	**Less Likely:**
Trust in State agency ($p=0.001$)	
Colorado resident ($p<0.01$)	
Descriptive norm ($p<0.05$)	

Perceived risk severity ($p<0.05$)
Attitude ($p<0.05$)
New Mexico Resident ($p<0.05$)
Montana Resident ($p=0.05$)

3.7 Significant Predictors of Compensation Use Intention

Trust, perceived risk, descriptive and personal norms, attitudes, and state of residence had the strongest relationship with compensation use intention for my surveyed population. A lack of trust in state agencies ($p<0.01$) was the strongest predictor of not intending to use compensation. Like reporting intention, the more financially vulnerable a respondent perceived to be (risk severity – $p<0.01$ mixed model, $p<0.05$ specific model), and the larger the percentage of neighbors and/or community members a respondent believed were already using, or would use compensation (descriptive norm – $p<0.01$ mixed model, $p<0.05$ specific model), the more likely their intention to use compensation. The more positive a respondent's attitude toward being compensated for depredation, the higher their intention ($p<0.05$), and respondents from Colorado ($p<0.01$), Montana ($p\leqq0.05$) and New Mexico ($p<0.05$) were more likely to intend to use compensation (Table 1.3). The older a respondent, the less likely their intention ($p<0.05$ mixed model significance only). The stronger a respondent's personal norm (their belief that reporting depredation helps keep an accurate record of wolf conflict) the more likely their intention to use compensation in the mixed model ($p=0.05$). Perceived behavioral control and beliefs about usefulness were not significant in any of the four models.

4 Discussion

4.1 Descriptive Statistics

Overall, I found high reporting rates across producers who had experienced wolf depredation, suggesting the producers surveyed are likely not contributing to any inaccuracy in reporting data used by agencies via low reporting rates. Compensation utilization was somewhat low among those who had experienced depredation (67%) but higher than what has been found in other studies (Lee et al. 2017). Attitudes about the reporting process were more positive than those about compensation, and the total surveyed population agreed more strongly that the compensation application process is difficult and time consuming (both perceived behavioral control) compared to those who had reported and/or applied for depredation compensation in the past. In general, respondents did not believe that the compensation application process was difficult, but did agree that the carcass detection and confirmation processes were time consuming; those with reporting experience agreeing more strongly.

Trust in both the state and federal government was greater than 50% for all respondents, for those with reporting experience, and for those with compensation experience, but less than 50% for environmental groups. Trust that the agency personnel investigating depredations were doing so fairly (trust in the personnel and process) was significantly higher among those with experience reporting and using compensation than the total surveyed population (about 30% higher). This may suggest that either those with existing trust are more likely to report and/or apply for compensation, or that the process of investigating a depredation with agency personnel can build trust in the process. About 15% more of those with reporting and compensation use experience agreed that they worry about wolf depredation (risk probability) compared to the total surveyed population, although about 10% more of the total population agreed their business would be financially vulnerable without compensation (risk severity).

4.2 Reporting and Compensation Use Intentions

Reporting and compensation use intentions were highest among those with compensation experience, (over 90%) and lowest among the total surveyed population, (around 80%). This high level of compensation use intention among respondents, along with the mixed levels of satisfaction with existing compensation programs may suggest that compensation for direct losses is valued among producers facing conflicts with wolves, even when administered through a program perceived to be dissatisfactory. If true, wildlife managers and policy makers should consider compensation for direct losses an important tool for addressing wolf-livestock conflict.

No factors related to compensation drove reporting intention, and only one reporting related variable – the personal norm – was correlated with compensation use intention (p=0.05). From a management perspective, it is favorable that compensation related variables are not influencing reporting rates, since high reporting rates lead to good data that can be used to create effective wolf management policies. It's possible that the community-scale benefits associated with reporting are overpowering any potential correlation between reporting and compensation factors. Compared to compensation use with almost exclusively operational or individual-scale benefits, depredation reporting can help neighboring operations by informing local wolf management, and operations region-wide by informing effective wolf policy. Participants in the focus group sessions described having a sense of personal responsibility to help keep accurate and up-to-date records of wolf conflict so that policies developed using that data would reflect what was happening on the ground.

4.3 Demographic Predictors

Older age was the only consistent demographic predictor of intention across all four models. The older a participant, the higher their reporting intention, but the lower their compensation use intention. This result compliments the findings of other wildlife-conflict reporting studies who found that older age was linked to increased reporting, more negative attitudes, and lower tolerance for carnivores (Hayman et al. 2014). This could reflect differences in values across age groups and generational cultural norms, what Heberlein (2012) calls the “cohort effect” (Hayman et al. 2014). If we are seeing this effect, wildlife agencies may see an increase in compensation use over the years as the younger cohort of livestock producers become a greater portion of the overall ranching population.

State of residence was only significant for the compensation models, where respondents from Montana, New Mexico, and Colorado were more likely to intend to apply for compensation. After the recent state-mandated wolf reintroduction, Colorado state producers are likely concerned about future wolf-conflict and related financial vulnerability. The uncertainty among the Colorado sub-population of what’s to come may have contributed to a desire for readily available financial assistance if/when wolf depredation occurs within my surveyed population. Alternatively, resource managers in Montana and New Mexico have been managing wolves for longer than other states like Washington, Oregon, California, and Colorado. Greater familiarity with wolves and the management of wolves might have given producers time to familiarize themselves with compensation, which would explain the positive relationship between Montana and New Mexico states with compensation use intention.

4.4 Attitudes, Beliefs about Usefulness, and Perceived Behavioral Control Predictors

Attitudes were only significant in the compensation models, which could reflect stronger dissatisfaction with compensation-related factors among respondents (e.g., amount paid, who supplies funding, application process) compared to reporting-related factors (e.g., detecting carcasses, having depredations confirmed). Overall beliefs about utility were high for reporting behavior, but very low for compensation, yet neither belief construct drove reporting or compensation use intention. Beliefs about behavioral control were also not in any model, which may suggest that constructs other than beliefs have stronger influence on both behavioral intentions.

4.6 Norm Predictors

In my survey, an individual's expectations of themselves to report depredation, as well as their perceptions of whether other people were reporting and using compensation were stronger drivers of behavioral intention than whether they believed their community and/or neighbors would support them reporting and/or applying for compensation. Like the findings of Van Eeden et al. (2020), norms and perceived risk were among the strongest drivers of both behavioral intentions. Unlike their findings, perceived risk factors were stronger predictors of compensation use intention than norms. Descriptive norms were significant in all four models, suggesting that perceptions about whether other producers are reporting and/or applying for compensation may drive behavioral intentions, and furthermore actual behavior.

The personal norm metric was significant in the mixed compensation model. Injunctive norms, while not selected as significant by the Ordinary Least Squares regression, were originally selected by the Lasso regressions in all four models (see Appendix). These findings support the conclusions of Niemiec et al. (2020) who found in their meta-analysis that personal and descriptive norms had a larger relative influence on conservation-related behavioral intentions than injunctive norms. They also support the findings of several studies that suggest the influence of descriptive norms on behavior is moderated by group identity (Terry and Hogg 1996). As group identification increases between individuals, individuals will seek to accentuate similarities between themselves and the group, which in turn influences group descriptive norms (Terry and Hogg 1996, Norman et al. 2005). However, other studies have been unable to provide evidence of the relationship between descriptive norms and group identity (Norman et al. 2005).

This result suggests that future research should include metrics for all three types of norms, and that increasing producer awareness about reporting and compensation use among other producers may most effectively increase the rates of both behavioral intentions, and hopefully the number of producers receiving compensation support. If norms are driving behavioral intentions across the total producer population (not just my surveyed population), then these intentions are best examined at the community scale as opposed to the individual producer. In their meta-analysis on social influence in the natural resources, Abrahamse and Steg (2013) argue that volunteers who help inform other community members on certain issues (known as the block leader approach) are particularly effective at spreading information because existing social networks are utilized to diffuse that information, and face-to-face interaction may make social influence more powerful. Wildlife managers and policy makers should focus efforts toward providing peer-to-peer knowledge sharing opportunities for producers to share their depredation-related experiences with one another, as these opportunities may more effectively increase behavior through building social norms than educational presentations provided by agency personnel.

4.7 Perceived Risk and Trust Predictors

Perceived risk constructs were significant in every model. Perceived financial vulnerability (perceived risk severity) was significant in both compensation models, and past experience with depredation (past experience with risk) was significant in both reporting models. Perceived risk probability was not significant in any model, although notably it was selected by the Lasso regression in both reporting models and the mixed compensation model (see Appendix). The prominence of risk severity specifically supports the findings of Hayman et al. (2012) Wilbur et al. (2018), Van Eeden et al. (2020) and Krester et al. (2009) who all found that perceived risk severity was more influential on behavior related to potentially dangerous wildlife than perceived risk probability.

The prominence of perceived risk factors overall may suggest a need among my surveyed population to increase individual control over depredation risk. Risk literature has long argued that as perceived control over a hazard increases, perceptions of risk will decrease (Slovic 1987, Kahan et al. 2007, Zajac et al. 2012). It’s possible that producers who don't perceive any benefit gained from predator presence feel a lack of autonomy and control over predator-livestock conflict and carnivore conservation policies (Boitani et al. 2010, Dickman et al. 2011, Borgstrom 2012, Lee et al. 2017). In their review of global financial incentives for predator conservation, Dickman et al. (2011) note: "Under a coexistence-with-conflict scenario, the international community retains the existence, economic, and ecosystem value provided by carnivores on private land, whereas local communities suffer the direct, indirect, opportunity, and cultural costs". To increase producer autonomy over the conservation and management processes that influence their lives, wildlife managers should consider co-producing policies and management strategies with livestock producers to ensure those policies and strategies serve landowner needs (Naugle et al. 2020). They might also consider providing multiple options for financial, resource, and technical support related to wolf depredation rather than one ex-post compensation option. Allowing producers to choose the support that best fits their operational needs and preferences would improve producer autonomy while simultaneously acknowledging the diverse operational contexts of ranching operations.

Experience with depredation (i.e., past experience with risk) was significant in both reporting models, although the relationship was negative, which was counter to my prediction. To examine further, I isolated responses that selected "unlikely" and "extremely unlikely" to reporting intention from the total population of respondents and compared responses to other questions. Of this subgroup, only 20% of respondents ($n=1$) had ever reported a wolf depredation, and their survey results showed a stronger distrust for state and federal government when compared to other subgroups or the total response population. Since past reporting was still high among this subgroup, this could suggest that negative experiences are influencing future reporting intention for some producers (Naughton-Treves et al. 2003, Davenport et al. 2007, Lee et al. 2017, Macon 2020). This relationship may also explain why a lack of trust in government was a leading predictor of intention in both compensation models (the lower the trust, the less likely the intention). For example, several producers in our focus groups expressed concern that state fish and wildlife agency staff were not confirming wolf depredations honestly so that wolves would not face lethal removal. Depredation investigations can be highly emotional and stressful events for all parties involved, where, as one focus group participant put it, “trust is built by the spoonful, and lost by the gallon”.

I did not find a direct relationship between trust in management processes and personnel (specifically the depredation investigation process) and reporting or compensation use intentions. This was supported by my finding that normative beliefs were stronger drivers of reporting intention than trust, which may mean that even without trust, producers report depredations because they believe they should, and because they believe that other producers are also reporting. In their study examining community trust in Forest Service natural resource management, Davenport et al. (2007) found that those with regular interaction with agency personnel are more likely to trust the agency, or to distinguish between trusting the agency and trusting the personnel. Although trust in the agency personnel investigating depredations (trust in the process and the personnel) did not drive either behavioral intention, Davenport et al. (2007) argue that increasing interpersonal trust between community members and agency personnel may improve trust in the agency overall. Wildlife agencies may want to increase the level of interaction between their personnel and the ranching community beyond depredation investigation as a way for indirectly improving trust in the agency as a whole. Davenport et al. (2007) recommend that these interactions be informal and provide opportunities for repeat interaction, but also warn that if these actions are perceived by community members to be negative, they can alternatively increase distrust. To encourage positive interactions over negative ones, the authors recommend agency personnel receive trainings on local norms, community values and knowledge, and that the agency seek opportunities to incorporate norms, values, and knowledge into local management policies and programs (e.g., hiring and/or contracting members of the local community, using local businesses and experts, etc. – Davenport et al. 2007).

4.8 Caveats and Future Research

My results were limited by several factors. Originally, I was going to distribute surveys by hand at three to five events for livestock producers west wide facilitated by Western Landowners Alliance in addition to using Qualtrics. Due to Covid restrictions, I moved the survey to a fully online format, which I believe may have negatively influenced response rates. Additionally, my snowball method for collecting survey responses may have biased my results. Since protecting anonymity was more important than tracking those who received the survey, I do not know the details of my response rate. It's possible that WLA members were more likely to respond to the survey than other livestock producers due to their existing engagement on landowner concerns. If my sample is biased toward WLA members, it could mean that certain statistics (particularly my descriptive statistics) are not accurately representative of the total producer population. For example, WLA members may be more likely to report, or to intend to report a depredation than non-members, or those who wouldn't report and/or use compensation may not have chosen to take the survey even after receiving it. WLA members may have also had higher levels of trust in agencies and environmental group due to their existing engagement. Future research should include in-person survey deployment, as I believe the trust built through initial interactions between myself and the producers would have improved response rates and increased my sample size. A truly random sample or stratified random sample would also benefit future research and the representational power of those findings.

5. Conclusion

The goal of this study was to gain an improved understanding of producer perspectives on wolf depredation reporting and compensation use, and to identify the factors driving reporting intention and compensation use intention. Depredation reports are the primary source of data used by wildlife agencies developing management protocols and policies for wolf-livestock conflicts. Until now, we knew very little about which factors drive reporting and compensation use intention for wolf depredation, and by extension, may drive actual behavior. Overall, my study found that wolf depredation reporting rates were high among my surveyed population. Future intentions to report and use compensation were also high, but compensation utilization among my surveyed population could be improved. The most common stated reasons for not reporting a depredation included a lack of trust regarding the depredation investigation confirmation process, discomfort with government oversight and regulation, and that the time investment (carcass detection and confirmation) was not worth the available compensation. The most common stated reasons for not using compensation included dissatisfaction with the depredation confirmation process (too much validation and paperwork), that the amount of compensation was not enough or worth the hassle of applying, too low of a payment, and a lack of trust and satisfaction with state government employees and their wolf management decisions. The strongest drivers of reporting intention among my population were descriptive norms and age (past experience with depredation significantly discouraged reporting intention). The strongest drivers of compensation use intention among my population were trust in state agencies, descriptive and personal norms, perceived risk severity, attitudes about being compensated, and being a Colorado, New Mexico, or Montana resident (age significantly discouraged compensation use intention). Future research should focus on how best agencies can reduce perceptions of risk associated with depredation and improve trust between themselves and the ranching communities facing wolf conflict. Reducing perceptions of risk may be best accomplished through providing compensation for depredation that is more representative of actual losses to wolves.

CHAPTER 2: EXPLORING LIVESTOCK PRODUCER INTEREST IN ALTERNATIVES TO COMPENSATION PROGRAMS FOR WOLF DEPREDATION

1 Introduction

1.1 Background

In November 2020, Proposition 114 – a ballot initiative designed to require Colorado Parks and Wildlife Commission develop a plan to reintroduce and manage grey wolves (*Canis lupus*) in Colorado state – passed by a half of one percentage point (Brasch 2020). Part of the preparations for reintroduction include the development of a compensation program for livestock producers who experience wolf-related conflicts. Wolf-livestock conflict can result in direct economic losses to the producer in the form of depredation (when wolves kill livestock) and indirect losses from predator-induced stress (reductions in seasonal weight gain in surviving animals, reduced reproductive rates, and injuries needing veterinary care – Treves and Karanth 2003, Breck 2004, Ramler et al. 2014, Erickson 2016). In addition, there can be large time, energy, and resource investments required by livestock producers to monitor both wolves and livestock in areas with conflict (e.g., working additional hours, hiring additional employees, changing grazing areas or turn out dates, etc. – Dickman et al. 2011, Hoag et al. 2011, Harris 2020).

To mitigate the negative impacts of wolf depredation on livestock operations, several government agencies, private businesses, and non-government organizations offer compensation programs that pay producers for confirmed wolf depredations (Naughten-Treves 2003, Muley and Musiani 2008, Dickman et al. 2011, Lee et al. 2017, Morehouse et al. 2018, Harris 2020, Macon et al. 2020). The primary objective of most compensation programs is to improve 1. tolerance for predators and foster coexistence, (measured as reduced retaliatory killings of predators, improved producer attitudes toward predators, and improved compliance with conservation protocols), and 2. the economic equity and viability of ranches facing wolf conflicts by distributing the costs of predators over a larger group (Harris 2020). How these programs are administered and funded varies widely, but most programs offer fair market price for the animal killed (Harris 2020). In general, compensation requirements include the following: producers must detect a carcass they suspect to be a wolf depredation, report the carcass to the agency running depredation investigations, the carcass must be confirmed as wolf caused (probable depredations are often also compensated for), and then the producer can submit a compensation application (Harris 2020). Additional requirements for compensation eligibility can include reporting carcasses within a strict timeframe after detection or adopting a predetermined number of conflict reduction tools (WDFW, WDGF).

Despite their intention, compensation programs are not always received well or utilized by the ranching community. Findings from Chapter 1 revealed that although most producers who responded to the survey intended to apply for compensation in the future (80%), only 69% of those producers who had experienced wolf depredation had applied for compensation, and satisfaction with current compensation programs was extremely mixed (see Chapter 1, Figure 1.2). Common sources of dissatisfaction include the level of evidence required to confirm a depredation as wolf caused, the amount of compensation not representing total losses to wolves, unreliable and unsustainable program funding, a lack of trust and satisfaction with state government employees and their wolf management decisions, and that the time and resources required for reporting and compensation application is not worth the amount paid (Montag et al. 2003, Sommers et al. 2010, Lee et al. 2017, Scasta et al. 2018). Several authors have also suggested that compensation programs are seen unfavorably by some livestock owners who perceive them as a public relations strategy that does not adequately capture the true cost of living with wolves (Nie 2001, Harris 2020).

1.2 Alternatives to Compensation Programs

Compensation programs are not the only financial instruments available to mitigate the negative impacts of wildlife on agricultural communities. Insurance schemes are programs where those at risk of depredation pay a premium at the start of the season. Those funds are then distributed across participating producers when they experience depredation (Harris 2020). Depending on the program, a potential benefit of insurance schemes is more consistent funding provided by producers than would normally be provided by the government (Harris 2020). A potential drawback is that participating producers must fund the program themselves, and during high-conflict years, funding may be depleted quickly (Miquelle et al. 2005, Karamanlidis et al. 2011, Morrison et al. 2013, Marino et al. 2018). In his discussion paper reviewing international compensation instruments, Harris found that most insurance schemes for livestock depredation were ultimately abandoned due to low payments, lack of participation, a need for subsidization, and low satisfaction among participants (Harris 2020).

Cost-sharing, while almost identical to insurance schemes when providing exclusively financial support, can also be used for technical assistance with conflict reduction tools (e.g., technical and/or material assistance with deploying and maintaining conflict reduction tools like fladry, fencing, range riders, guard dogs, and carcass removal). For example, Defenders of Wildlife provides 50% of the funding needed to support the implementation of nonlethal tools as part of the Wolf Livestock Demonstration Project (Gade 2014). Ostensibly, a cost-share would face many of the same benefits and challenges as an insurance scheme unless participants were particularly interested in having access to conflict reduction tools. Karlsson and Sjostrom (2011) found that having access to subsidized tools in Sweden increased tolerance for wolves among livestock producers, while Larson et al. (2016) found producers were unhappy with a similar cost-share option.

Stemming from the idea of Payment for Ecosystem Services (Jack et al. 2008), Payment for Presence is an alternative to traditional depredation compensation where livestock producers are paid proactively based on coexisting with predators (Nelson 2009, Macon 2020). A potential benefit to this type of program is that producers are paid whether they face depredation or not, which means some of the indirect losses associated with wolf presence can be compensated for (Dickman et al. 2011, Macon 2020). In these programs, coexistence is usually measured through predator population estimates. Some studies have found these programs to be cheaper long term than traditional compensation if the predators in question are not difficult to detect (Nistler 2007, Schwerdtner and Gruber 2007). From a carnivore conservation perspective, incentivizing producers to manage for carnivore abundance may sound like an effective solution, however several of our focus group participants expressed that this model does not align with their values or needs: “I don’t raise cattle to feed wolves and bears” was a common response, and some participants noted that Payment for Presence can feel like a one-sided tolerance request (Brown 2008). Incentivizing coexistence without addressing conflict may increase cultural divides, ultimately decreasing satisfaction and engagement from the agricultural community (Madden 2004).

Habitat Leasing is a similar, yet alternative option to Payment for Presence. Habitat Leasing pays producers for maintaining or improving habitat on a systemic scale that, through extension should also benefit predator species (Nelson 2009, Zabel and Roe 2009, Can et al. 2014, Kreye et al. 2017, Macon 2020). Although not currently organized around predator-livestock conflict, the Grasslands Conservation Reserve Program run by the USDA Farm Service Agency serves as a model for this alternative, where grazing operations are paid by the acre based on habitat quality and quantity assessments (GCRP 2021). Unlike Payment for Presence programs, this approach acknowledges the potential array of benefits and ecosystem services grazing operations can provide for rangeland habitats both through management techniques and preventing development (Krausman et al. 2009, York et al. 2019). Unlike managing exclusively for healthy predator populations, these habitat benefits are also relevant to the producer’s bottom line, since high quality and quantity water sources, riparian habitat, and forage also improve weight gain and health in grazing livestock. By fostering overall habitat quality, prey species, predator species, and domestic animals can all benefit.

Very few examples of these alternatives have been studied, and little to no empirical evidence exists on their affordability or effectiveness compared to traditional compensation programs (Harris 2020). We also lack sufficient data on whether producers are interested in compensation alternatives (Montag et al. 2003, Naughton-Treves et al. 2003, Treves and Bruskotter 2014, Larson et al. 2016). I wanted to help address this research gap by exploring producer perspectives of existing compensation programs. My research questions were: 1. *What are livestock producer perspectives on existing* *compensation programs for wolf depredation?* and *2. What alternatives to existing support programs (like depredation compensation) are producers interested in?* My hope is that these findings will help Colorado Parks and Wildlife and other western wildlife agencies design and/or modify producer support programs to sustain working lands, connected landscapes, and native species.

1.3 The Theory of Discrete Choice Modeling

To better understand livestock producer interest in compensation program alternatives, I simplified a Discrete Choice Experiment design into a Choice Question deployed as part of a larger survey. This survey targeted North American livestock producers experiencing wolf conflicts (Chapter 1). Discrete Choice Experiments ask participants to select their most preferred option from a series of potential options. These options are coded and presented to respondents in a way that requires the weighing of tradeoffs and allows researchers to analyze preference for individual characteristics of each option (Bond et al. 2011, Holmes et al. 2017). These experiments are based on the Random Utility Behavioral Model, which states that an individual will choose the option (be it a job, program, or policy) they associate with the highest utility (aka benefit or satisfaction – de Bekker-Grob et al. 2012). Discrete Choice Experiments can be used to measure the relative importance of individual attributes (e.g., statistical significance or direction) tradeoffs between attributes, (e.g., how much of one attribute is a participant willing to give up for the improvement of another) and the probability of take-up of certain combinations of attributes (Lagarde and Blaauw 2009, de Bekker-Grob et al. 2012, Holmes et al. 2017). This level of analysis requires an extensive series of questions be presented to each participant (sometimes up to 30 different choice sets). Since my Choice Question was designed as an addition to a much larger survey on wolf depredation and compensation, I chose to modify and simplify the Discrete Choice Question design to prevent participant overwhelm and fatigue (Porter et al. 2004).

2 Methods

2.1 Study Area

I deployed the simplified Choice Question as part of a larger study looking at motivators for wolf depredation reporting behavior and compensation use intention (Chapter 1). I distributed the survey across all Western, mainland states with active wolf populations: Washington, Oregon, California, Idaho, Montana, Wyoming, Colorado, Arizona, and New Mexico. I included Alberta, Canada due to its proximity and similar socioecological system of wolf-livestock conflict (see Chapter 1, Table 1.1 for state-specific compensation program summaries adapted from Harris 2020).

2.2 Survey and Choice Question Design and Implementation

To inform the development of our survey questions, our team facilitated twelve virtual focus groups and five unstructured interviews with livestock producers in Wyoming, Montana, New Mexico, Arizona, Oregon, and California from June through October 2020 (Weiss 1995). Through these sessions, we identified what aspects of traditional compensation programs, and what characteristics of alternative programs producers were interested in. A key finding from these sessions was that overall, participants believed an ideal program would have various support and/or payment options that a producer could choose to participate in. This finding supports the work of Dickman et al. (2011) who, after reviewing financial instruments for predator conservation across the globe, suggested a combination of approaches would be most successful. For this reason, I designed my modified Choice Question to have varying levels of all three of the most popular types of producer support identified by participants: compensation for direct losses (depredation compensation), a Habitat Lease, and a Cost-Share with financial and/or technical assistance. I used these focus group sessions to also identify reasonable and actionable levels for each of the three types of producer payment.

To vary compensation for direct losses, I used a multiplier. Some depredation compensation programs use multipliers added to the fair market value of a depredated animal to account for depredations never detected by the producer. For example, Wyoming compensates producers seven to one for losses within the game management area near Yellowstone National Park but compensates without a multiplier for losses outside that area (Harris 2020). This high of a multiplier is extremely rare, with most programs compensating at or around fair market value. Although how large a multiplier should be is still hotly debated (Oakleaf et al. 2003, Lee et al. 2017, Sommers et al. 2010, Breck et al. 2011, Morrison et al. 2013) landscape characteristics, climate, weather, operational capacity, scavengers, and the type of livestock grazed can all influence carcass detectability, and therefore whether producers can report depredations for compensation. To vary levels of depredation compensation, I used the following options: no payment for depredation, payment at fair market value, and payment at fair market value with a multiplier of three. To vary the Habitat Lease payment option, I adjusted the dollar amount per acre. The levels from lowest to highest were: no Habitat Lease option, a Habitat Lease paying five to nine dollars per acre annually, and a Habitat Lease paying ten or more dollars per acre annually. Finally, the levels for the Cost-Share option were: Cost-Share available, and Cost-Share unavailable (Table 2.1).

Table 2.1 *Choice Question: All five potential producer support programs with varying levels of each payment option (characteristics/attributes) as presented to participants in the survey. Participants were forced to select one program option only.*

Programs	**Payment Option 1:** Payment for Direct Losses	**Payment Option 2:** Habitat Lease that does not displace livestock	**Payment Option 3:** Cost Share Program for wolf conflict prevention tools
1	Fair Market Value with a multiplier of 3	Not available	Financial assistance and technical assistance provided with cost-sharing
2	Fair Market Value	$5 - $9 /acre annually based on geographic location	Financial assistance and technical assistance provided with cost-sharing
3	Not available	$10 or more /acre annually based on geographic location	Financial assistance and technical assistance provided with cost-sharing
4	Fair Market Value	$10 or more /acre annually based on geographic location	No assistance available
5	Fair Market Value with a multiplier of 3	$5 - $9 /acre annually based on geographic location	No assistance available

To supplement the Choice Question, I included fifteen additional questions related to compensation program characteristics – thirteen before the choice question (see Table 2.2), and two following immediately after the choice question to improve my understanding of respondent satisfaction with the selected program: 1. “To what extent would you be satisfied with the program you selected as most preferrable?” presented on a five-point Likert scale ranging from “extremely satisfied” to “extremely unsatisfied”, and 2. “Keeping in mind that resources are limited, what could be changed about the program you selected as your most preferred option to make the program even more preferrable?” presented as an open-ended, text-entry response.

Livestock producers, wildlife managers, researchers, and non-government organization staff reviewed a draft of the survey after approval by the Colorado State University Institutional Review Board (protocol # 20-10064H). Specific attention was given to the modified Choice Question to ensure that programs with varying levels of each payment option were both desirable and actionable by policy (de Bekker-Grob et al. 2012). The survey went live December 2020 via Qualtrics (Provo, UT), a licensed online survey platform (Couper 2001, Chang and Krosnick 2009, Lowry et al. 2016). I used purposive sampling via snowballing to distribute the survey (Teddlie and Yu 2007).

Western Landowners Alliance attracts members with diverse perspectives on wolf depredation and compensation, which we confirmed through our focus group sessions and unstructured interviews with the Alliance’s members. We emailed an anonymous link of our survey to all the Alliances’ members, more than 200, followed by emails to state and county-level Cattlemen’s, Wool, and Beef Growers' Associations, State and Tribal Farm Bureaus, Extension agents from western universities, and wildlife agency personnel to ensure a representative cross-section of producers and to limit voluntary response bias (Dillman et al. 2014). After completing the survey, participants were encouraged to share the survey link with other livestock producers west-wide (Etikan et al. 2016). We sent two reminder emails in January and March, then closed the survey in May 2021 with a total of *n=165* responses. I analyzed qualitative responses using a simplified version of inductive thematic content analysis (Braun and Clark 2006, Niemiec et al. 2020).

Before seeing the Choice Question, survey participants were provided with a description of each payment option (see Appendix). After review, participants were presented the Choice Question and asked to select the program they would most prefer to participate in (Table 2.1 – programs one through five). The survey forced participants to select only one program, intentionally encouraging respondents to negotiate the tradeoffs between each of the five programs.

3 Analysis

To gain a better understanding of the potential difference in perspective between those who have used compensation before and those who have not, I stratified my responses into two groups for comparison: those who had applied for compensation in the past that I reference from here forward as my compensation subgroup, and those who had not, referenced as my total surveyed population.

I analyzed my qualitative response question ("Keeping in mind that resources are limited, what could be changed about the program you selected as your most preferred option to make the program even more preferrable?") using inductive thematic analysis (Marshall and Rossman 1998, Braun and Clark 2006, Niemiec et al. 2020). Inductive thematic analysis is a qualitative data analysis technique where themes are derived from the data themselves as opposed to being predetermined (Marshall and Rossman 1998). For these questions, I categorized and coded distinct responses until saturation of categories was met, and response frequencies achieved (Niemiec et al. 2020 – see Appendix for details).

4 Results

4.1 Summary Statistics

I removed survey responses with thirty percent or more of the questions unanswered prior to analyses (total *n=165)*, resulting in 127 responses (Niemiec et al. 2020). Sixty-nine percent of respondents who had experienced wolf depredation had applied for compensation in the past (30% of total respondents). Perspectives on the compensation process, compensation amount, and program management varied between respondents who had experience with depredation compensation and those who did not (Table 2.2). Overall, producers with compensation experience (the compensation user subgroup) agreed more strongly that they could trust the depredation confirmation process, but also agreed more strongly that detecting depredated carcasses was time consuming. Both the total respondent population and the compensation user subpopulation did not agree that the application process was difficult or time consuming. Levels of agreement were moderate across both surveyed populations regarding the extent of financial vulnerability caused by depredation, but both populations agreed more strongly that the compensation available to them was not representative of their actual losses to wolves (including the need for a multiplier and compensation for indirect losses).

More producers with compensation experience agreed that a multiplier was needed than agreed that compensation for indirect losses was needed, although across both populations, about 80% of producers agreed that indirect losses were as, or more damaging than direct losses. Seventy-seven percent of all respondents believed that in addition to direct losses, livestock producers should be compensated for indirect losses. More compensation users believed undetected depredations and stress-induced reductions in weight gain were influencing their economic losses than the total population of respondents (who were more concerned about lowered reproduction rates). Both surveyed populations agreed on who should fund, and who should administer compensation programs and conflict mitigation strategies (Table 2.2). The majority of respondents believed wolf advocates and federal tax dollars should pay for compensation programs, not the producers themselves, and state agricultural departments were the most selected for organization to administer compensation programs.

Table 2.2 *Constructs and comparison of responses to survey questions between the total surveyed population and compensation user subgroup.*

Construct:	Out of Total Respondents:	Out of Compensation Users Subgroup:
Compensation Process: (Agree – Strongly Agree)		
I trust the personnel investigating a wolf depredation to investigate fairly	44%	76%
Detecting carcasses depredated by wolves is time consuming	69%	82%
Having carcasses confirmed by the required personnel as wolf depredations is time consuming	76%	79%
The process of applying for wolf depredation compensation is difficult	29%	18%
The process of applying for wolf depredation compensation is time consuming	42%	26%
Compensation Amount: (Agree – Strongly Agree)		
Without compensation for wolf depredations, my business would be financially vulnerable	35%	26%
The amount of compensation available to me for wolf depredations is representative of my actual losses	12%	26%
In addition to compensation for direct losses, (depredations) I believe livestock producers should be compensated for indirect losses	68%	58%
I believe a multiplier would more accurately represent my losses	65%	82%

Which of the following do you consider part of economic losses to wolves? (Most selected to least selected)	1. Depredations 2. Stress induced lower reproductive weights 3. Stress induced reductions in weight gain 4. Undetected depredations 5. Injuries and vet care	1. Depredations 2.Undetected depredations and stress induced reductions in weight gain (tied) 3. Stress induced lower reproductive rates 4. Injuries and vet care
Are direct or indirect losses more financially damaging?	Direct – 6% Indirect – 22% They are equal – 58%	Direct – 11% Indirect – 18% They are equal – 63%
Program Management: (Most preferred to least preferred)		
Who should fund programs?	1. Wolf advocates 2. Federal tax dollars 3. Recreationists/State tax dollars (tied) 4. Hunting licenses 5. Private insurance 6. Livestock Producers	1. Wolf advocates 2. Federal tax dollars 3. Recreationists 4. State tax dollars 5. Hunting licenses 6. Private insurance 7. Livestock Producers
Who should administer programs?	1. State Ag department 2. USDA 3. State Wildlife Agency 4. Fish and Wildlife Service 5. Elected county officials 6. Elected local volunteers 7. NGO	1. State Ag department 2. USDA 3. State Wildlife Agency 4. Fish and Wildlife Service 5. Elected county officials 6. Elected local volunteers 7. NGO

4.2 Choice Question

N=117 respondents answered the Choice Question (see Table 2.1 for program details). Program one was the most popular across total respondents (32% - see Figure 2.1) followed closely by program two (31%), program five (24%), program four (10%) and lastly program three (3%). For the compensation user subgroup, program five was the most popular selection (31%) followed by program two (29%), program one (26%), program four (14%) and finally program three (0%). Experience with depredation and compensation use varied minimally across selected programs, as did levels of self-reported satisfaction with the program selected. Program three was the only exception, where selectors from the total respondent population had never experienced wolf depredation *(n=2*), and overall reported levels of satisfaction were low. When asked what changes they would make to their selected option to increase satisfaction, the most common responses were an increase in lethal control for wolves, a higher multiplier, improved access to conflict reduction tools (nonlethals), and adding compensation for indirect losses (see Appendix). Other common non-program specific responses included funding programs through the communities who want wolves on the landscape, and ensuring that programs are adaptive to change with consistent, stable funding.

Chart 1: Program Selection from the Total Population

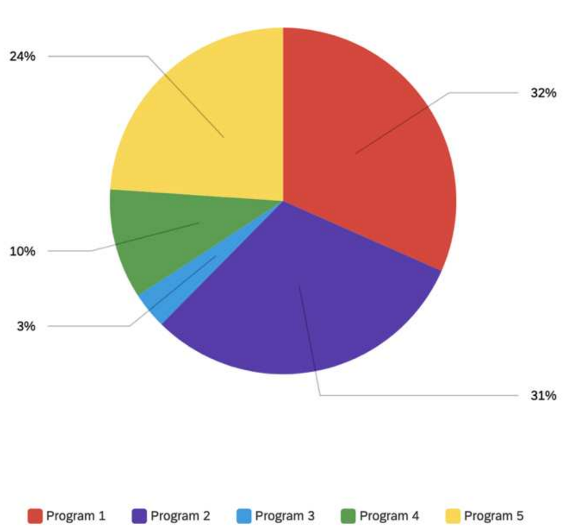

Chart 2: Program Selection from the Compensation User Subgroup

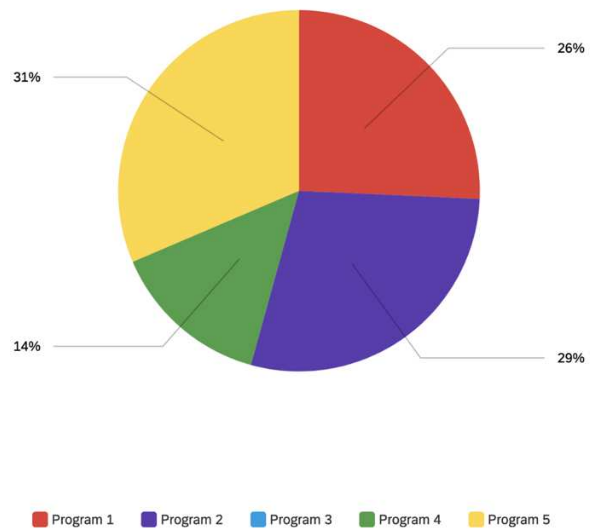

Figure 2.1: *Choice Question program preference selected by the total survey population (chart 1) and the compensation user subgroup (chart 2). Program 1: Payment for direct losses at 3 times fair market value, no habitat lease option, and financial assistance and technical assistance provided through a cost-share for conflict prevention tools. Program 2: Payment for direct losses at fair market value, a habitat lease option that pays $5-$9 per acre, and financial assistance and technical assistance provided through a cost-share for conflict prevention tools. Program 3: No payment for direct losses, a habitat Lease option that pays $10+ per acre, and financial assistance and technical assistance provided through a cost-share for conflict prevention tools. Program 4: Payment for direct losses at fair market value, a habitat lease option that pays $10+ per acre, and no financial assistance or technical assistance provided through a cost-share. Program 5: Payment for direct losses at 3 times fair market value, a habitat lease option that pays $5-$9 per acre, and no financial assistance or technical assistance provided through a cost-share.*

5 Discussion

5.1 Producer Perspectives on Compensation Programs

Similar to other studies that surveyed livestock producers, compensation utilization among my surveyed population was low among producers experiencing wolf depredation. This may suggest that although producers are not completely satisfied with compensation programs, they may value being compensated for direct losses to wolves (Maheshwari et al. 2014, Lee et al. 2017). My findings on producer perceptions of my surveyed population support several other studies that argue depredation can have significant, and varied financial impacts on producers including direct losses from depredation, indirect losses from predator presence, and the time and resource requirements needed to monitor livestock-predator conflict; all of which should be considered in the development of a compensation or producer support program (Muhly and Musiani 2009, Dickman et al. 2011, Hoag et al. 2011, Lee et al. 2017, Macon 2020).

5.2 Choice Question Program Selection

Program one (depredation compensation at a multiplier of three, no Habitat Lease, and a Cost-Share available) and program two (depredation compensation without a multiplier, Habitat Lease at five to nine dollars per acre, and a Cost-Share available) were the most selected producer support program across the total surveyed population. These programs are very similar as both provide a way to account for losses outside of detectable depredations like indirect losses (see Chapter 1). Which payment option is most effective at providing needed support – a Habitat Lease or multiplier – may be specific to the context of an individual operation (more below). Interestingly, programs four and five provided higher payment for indirect losses and/or undetected carcasses than programs one and two, but programs four and five did not provide a Cost-Share for financial and technical assistance with conflict reduction tools. This may suggest that producers are interested in using nonlethal methods to reduce conflicts, even at the expense of higher support payments. Programs one, two, four, and five all provided compensation for depredation, even if only at fair market value. This finding directly contradicts concerns expressed in other studies that paying producers for losses (instead of incentivizing producers to prevent conflict) will result in a lack of motivation to coexist with predators (Dickman et al. 2011, Chervier et al. 2019, Macon 2020). If that had been the case in my surveyed population, I would have expected to see a higher preference for programs four and five that paid more overall, and without the necessary implementation and upkeep associated with conflict reduction tools.

However, low preference for program three may signal an important aspect to the above finding. Program three was the only program without depredation compensation. Despite having a very high payment per acre amount and a Cost-Share available, program three had only 3% preference and low levels of satisfaction. That means that 97% of respondents wanted access to depredation compensation, even at the expense of higher payments per acre as part of a Habitat Lease, or access to a Cost-Share. This may reflect the importance of compensation for direct losses, and potentially critical role depredation payments play in an effective producer support program. Unlike Payment for Presence or Habitat Lease options, depredation compensation provides measurable, mostly guaranteed support when wolf depredation happens. The challenge with providing only incentive-based options like Habitat Leasing is that wolf depredation varies significantly on spatial and temporal scales (Lee et al. 2017, Hanley et al. 2018, Pimenta et al. 2018, Clark et al. 2020). Lee et al. (2017) found that in Alberta, calf depredations ranged from 0-25% across all producers in the province, but 2.6% of producers experienced calf depredation losses greater than 10% annually, meaning a single producers' experience with depredation (and resulting losses) may differ greatly from their neighbor one year, and not at all the next. Depredation compensation as one part of a program with diverse payment and engagement options protects the producers hit hardest by wolves through providing additional support when nonlethal strategies are not enough (Moreira-Arce et al. 2018). This is a critical finding for wildlife managers and policy makers who may need to consider the vulnerability involved with a 'one size fits all' approach to producer support. Even if interest in alternatives exists among producers, my results may suggest that depredation compensation should be available so that the uneven impacts of wolf depredation year to year can be accounted for equitably across operations.

Part of the challenge with designing an effective producer support program may be the unique, contextual needs of each operation. For example, participants from our focus groups described situations where compensation for direct losses alone was not effective for their operation because of grizzly bears. At these locations, grizzly bears either ate or scavenged carcasses so quickly and thoroughly, detecting carcasses to even report was described as "impossible". Alternatively, producers from the southwestern states expressed hesitation about relying exclusively on a Habitat Lease that would require regular reevaluation of habitat benefits. In their operational context, wildfire, drought, and year-round grazing make evaluating habitat health difficult on short, annual timeframes, yet necessary for accurate evaluation. Challenges were not region-specific, as multiple participants across the West expressed frustration with not being able to afford additional employees to look for reportable carcasses. Although no one program will work for every livestock producer facing carnivore conflicts, programs with diverse payment and engagement options can provide flexibility for the context-specific needs of each operation, while also helping to cover additional conflict-related costs. This flexibility may also help to support landowner autonomy and ownership over wolf-related management needs, addressing the problematic top-down nature of compensation program development and many wolf-related conservation policies (Boitani et al. 2010, Borgstrom 2012, Lee et al. 2017, Macon 2020).

5.3 Management Implications and Future Research

My findings suggest that my surveyed population of livestock producers want support programs for wolf-livestock conflict with diverse payment and engagement options that equitably address the needs of different operations. While respondents expressed interest in alternatives to traditional compensation, 97% of respondents preferred a support program with depredation compensation. Wildlife managers and policy makers should include depredation compensation as part of support programs to protect against the uneven, and often unpredictable influence of wolf depredation. Future research should utilize a full Discrete Choice Experiment to evaluate producer interest in not only different payment methods, but also the relative importance of individual attributes (e.g., what multiplier best represents my losses) tradeoffs between attributes (e.g., how low am I willing to go on a multiplier for a higher payment per acre on a Habitat Lease) and the probability of take-up of certain combinations of attributes (Lagarde and Blaauw 2009, de Bekker-Grob 2012, Holmes et al. 2017). Future research should also focus on evaluating the effectiveness of conflict reduction tools, as producer preference for programs with a Cost-Share for financial and technical assistance with nonlethal tools was high.

5.4 Caveats

My results were limited by several factors. Originally, I was going to distribute surveys by hand at three to five events for livestock producers west wide facilitated by Western Landowners Alliance in addition to using Qualtrics. Due to Covid restrictions, I moved the survey to a fully online format, which I believe may have negatively influenced response rates. Additionally, my snowball method for collecting survey responses may have biased my results. Since protecting anonymity was more important than tracking those who received the survey, I do not know the details of my response rate. It's possible that WLA members were more likely to respond to the survey than other livestock producers due to their existing engagement on landowner concerns. If my sample is biased toward WLA members, it could mean that certain statistics (particularly my descriptive statistics) are not accurately representative of the total producer population. For example, WLA members may have higher levels of trust in agencies and environmental groups due to their existing levels of engagement. Future research should include in-person survey deployment, as I believe the trust built through initial interactions between myself and the producers would have improved response rates and increased my sample size. A truly random sample or stratified random sample would also benefit future research and the representational power of those findings.

6 Conclusion

The goal of this study was to gain an improved understanding of producer perspectives on existing compensation programs for wolf depredation, and to identify producer interest in alternatives to existing programs. By using a simplified Discrete Choice Question, I was able to force participants to negotiate tradeoffs between different aspects of potential producer support programs for wolf conflict. Overall, my study found that 69% of respondents who had experienced wolf depredation had applied for compensation. In general, survey respondents did not find the compensation application process difficult or time consuming, but those in the compensation user subgroup believed more strongly that a multiplier was needed for undetected depredations compared to the total surveyed population. Eighty percent of all surveyed respondents agreed that indirect losses were as, or more damaging than direct losses. Who respondents believed should fund and administer compensation programs did not vary between the total respondents and the compensation user subgroup.

The most popular program selection among total respondents was program one (depredation compensation with a multiplier of three, no Habitat Lease option, and a Cost-Share available). Among the compensation user subgroup, the most popular program was program five (depredation compensation with a multiplier of three, a Habitat Lease option paying five to nine dollars per acre, and no Cost-Share available). Overall, I found that producers who took the survey value depredation compensation as part of a support program for wolf conflict, as well as a Cost-Share option for technical and financial assistance with conflict reduction tools. The most common stated changes to selected programs to increase favorability were an increase in lethal control for wolves, a higher multiplier, improved access to conflict reduction tools (nonlethals), adding compensation for indirect losses, funding programs through the communities who want wolves on the landscape, and ensuring that programs are adaptive to change with consistent, stable funding. My findings suggest that future research should utilize a full Discrete Choice Experiment to evaluate producer interest in not only different payment methods, but also the relative importance of individual attributes, tradeoffs between attributes, and the probability of take-up of certain combinations of attributes.

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APPENDICES

1 Codebook for Depredation and Compensation Survey – Chapter I.

VARIABLE (NAME)	VALUES	TYPE
Reporting Experience	1. Yes 2. No 3. I'm not sure	Categorical
"Why did you report the depredation(s)?" or "Why did you choose not to report the depredation(s)?"	Open-ended	Text entry
Reporting Attitude	1. Extremely positive 2. Positive 3. Neither positive or negative 4. Negative 5. Extremely negative	Ordinal (Likert)
Reporting Perceived Behavioral Control	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Reporting Injunctive Norm	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Reporting Descriptive Norm	1. 25% or less 2. 25% - 50% 3. 50% - 70% 4. 75% or more	Ordinal (Likert)
Reporting Personal Norm	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree	Ordinal (Likert)

	7. Strongly disagree	
Reporting Usefulness Belief	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Reporting Belief about Detecting Time	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Reporting Belief about Confirming Time	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Future Reporting Intention	1. Extremely likely 2. Likely 3. Neither likely or unlikely 4. Unlikely 5. Extremely unlikely	Ordinal (Likert)
Compensation Experience	1. Yes 2. No 3. I’m not sure	Categorical
“Why did you choose not to apply for compensation for the depredation(s)?”	Open-ended	Text entry
Compensation Attitude	1. Extremely positive 2. Positive 3. Neither positive or negative 4. Negative 5. Extremely negative	Ordinal (Likert)
Compensation Satisfaction “How satisfied are you with your current or past compensation program?”	1. Completely satisfied 2. Mostly satisfied 3. Somewhat satisfied 4. Neither satisfied or dissatisfied 5. Somewhat dissatisfied 6. Mostly dissatisfied 7. Completely dissatisfied	Ordinal (Likert)

Compensation Perceived Behavioral Control	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Compensation Injunctive Norm	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Compensation Descriptive Norm	1. 25% or less 2. 25% - 50% 3. 50% - 70% 4. 75% or more	Ordinal
Compensation Usefulness	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Compensation Ease	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Future Compensation Use Intention	1. Extremely likely 2. Likely 3. Neither likely or unlikely 4. Unlikely 5. Extremely unlikely	Ordinal (Likert)
Trust in the process	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Trust in Federal Government	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree	Ordinal (Likert)

	5. Somewhat disagree 6. Disagree 7. Strongly disagree	
Trust in State Government	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Trust in Environmental Groups	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Risk – Past Experience	1. Yes 2. No 3. I'm not sure	Categorical
Risk – Perception of Risk Potential	1. Extremely worried 2. Moderately worried 3. Somewhat worried 4. Slightly worried 5. Not at all worried	Ordinal (Likert)
Risk – Perception of Risk Severity	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
Demo – State	1. Arizona 2. California 3. Idaho 4. Montana 5. New Mexico 6. Oregon 7. Washington 8. Wyoming 9. Other	Categorical (text entry for "other")
Demo - Age	1. 18 or younger 2. 19 – 29 3. 30 – 49 4. 50 – 69 5. 70 or older	Ordinal

Demo - Gender	1. Male 2. Female	Categorical
Demo – Number of Head	1. 500 head or less 2. Between 500 and 1,000 head 3. Between 1,000 and 3,000 head 4. 3,000 head or more	Ordinal
Demo – Type of Livestock	1. Cattle 2. Sheep 3. Goats 4. Other	Categorical (select all that apply – text entry for "other")
Demo – Grazing Lands	1. Public 2. Private 3. Other	Categorical (select all that apply – text entry for "other")

2 Codebook for Depredation and Compensation Survey – Chapter II.

VARIABLE (QUESTION)	VALUES	TYPE
"I trust the personnel investigating a wolf depredation to investigate fairly."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"Detecting carcasses depredated by wolves is time consuming."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"Having carcasses confirmed by the required personnel as wolf depredations is time consuming."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"The process of applying for wolf depredation compensation is difficult."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"The process of applying for wolf depredation compensation is time consuming."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"Without compensation for wolf depredations, my business would be financially vulnerable."	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
"The amount of compensation available to me for wolf depredation	1. Strongly agree 2. Agree 3. Somewhat agree	Ordinal (Likert)

is representative of my actual losses to wolves.”	4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	
“In addition to compensation for direct losses, (depredations) I believe livestock producers should be compensated for indirect losses (weight loss, decreased reproductive rates, increased abortion rates, and veterinary bills for injuries caused by wolves).”	1. Strongly agree 2. Agree 3. Somewhat agree 4. Neither agree or disagree 5. Somewhat disagree 6. Disagree 7. Strongly disagree	Ordinal (Likert)
“Do you believe a multiplier would more accurately represent your direct losses to wolves?”	1. Yes 2. No 3. I’m not sure	Categorical
“Which of the following do you consider part of economic losses to wolves:”	1. The fair market value of depredated livestock 2. The fair market value of livestock depredated but never found 3. Veterinary costs associated with wounded animals, (indirect losses) 4. Weight loss in surviving animals due to stress, (indirect losses) 5. Lower reproductive rates and/or higher abortion rates in surviving animals due to stress, (indirect losses)	Categorical (select all that apply)
Which one of the following best describes how you feel about direct and indirect losses associated with wolf presence?	1. Direct losses are more financially damaging than indirect losses 2. Direct losses are less financially damaging than indirect losses 3. Direct and indirect losses are equally damaging 4. I’m not sure	Categorical
Please rank the following groups in order of who you believe should fund conflict prevention tools and strategies for reducing wolf-livestock conflicts, (including depredation compensation).	1. Wolf advocates 2. Federal tax dollars 3. Recreationists/State tax dollars 4. Hunting licenses 5. Private insurance	Categorical

	6. Livestock Producers	
Please indicate your level of interest in the following: A compensation program for wolf depredations run by your: 1. State wildlife agency 2. Federal Fish and Wildlife Agency 3. County officials 4. NGO or conservation organization 5. Local, community-elected volunteers 6. USDA 7. State department of Agriculture	1. Extremely interested 2. Somewhat interested 3. Neither interested or uninterested 4. Somewhat uninterested 5. Extremely uninterested	Ordinal (Likert)
“Which program would you most prefer to participate in?”	1. Option 1 2. Option 2 3. Option 3 4. Option 4 5. Option 5	Categorical
“To what extent would you be satisfied with the program you selected as most preferable?”	1. Completely satisfied 2. Mostly satisfied 3. Somewhat satisfied 4. Neither satisfied or dissatisfied 5. Somewhat dissatisfied 6. Mostly dissatisfied 7. Completely dissatisfied	Ordinal (Likert)
“Keeping in mind that resources are limited, what could be changed about the program you selected as your most preferred option to make the program even more preferable?”	Open – ended	Text entry

3 Inductive Thematic Analysis Results for Qualitative, Text-entry Questions

Chapter I.

Question 10: Why did you choose to report the wolf depredation(s)?

1. To confirm the species responsible – **n=11**
2. To keep good records of wolf depredation/conflict (neigh and the gov) – **n=10**
3. To be able to apply for compensation – **n=23**
4. Because I had losses and it's my job to protect my animals – **n=1**
5. Because it's required by law – **n=3**
6. So that management action on the wolves could be taken – **n=15**

Question 13: Why did you choose not to report the wolf depredation(s)?

1. Time consuming and/or too much of a hassle – **n=4**
2. Compensation not available – **n=1**
3. I enjoy wolves, depredations are the cost of having them – **n=1**
4. Too difficult to get a wolf confirmation/work with agency personnel on confirmation – **n=7**
5. I couldn't determine cause of death – **n=2**
6. I don't want attention on my operation (gov and other) – **n=4**

Question 39: Why did you choose not to apply for wolf depredation compensation?

1. I have not yet experienced wolf depredation – **n=21**
2. Depredations are a natural part of raising livestock/up to me to adapt/adjust – **n=2**
3. Compensation is not available/I did not qualify to apply – **n=4**
4. Compensation is not enough – **n=1**
5. Compensation is against my ethics – **n=3**
6. Application and reporting process is a hassle/not worth the amount available – **n=10**
7. I handle wolves myself – **n=1**
8. I don't want the attention on my operation/ I don't trust the state (gov and other) – **n=4**
9. I don't know how to apply – **n=1**

Chapter II.

Question 64: Keeping in mind that resources are limited, what could be changed about the program you selected as your most preferred option to make the program even more preferable?

1. Add payment for Indirect losses/ higher payment – **n=6**
2. Nothing – **n=6**
3. Not sure – **n=6**
4. Need prevention tools/nonlethals – **n=8**
5. Need more lethal removal/ more support for lethal – **n=15**
6. Add a multiplier/ bigger multiplier – **n=12**
7. Need a higher price/acre – **n=5**
8. A lease makes us nervous about government regulations/stipulations – **n=1**
9. Funding for these programs needs to come from demographics most intent on having wolves on the landscape – **n=8**
10. Local authorities should run compensation programs – **n=2**
11. Anything that provides sustainable funding – **n=4**
12. Adaptive programs – **n=7**
13. Add a cost-share – **n=1**
14. I'm not interested in a program, preventing depredation is my responsibility – **n=1**

4 Lasso-Selected Variables for all four Theory of Planned Behavior models (with Ordinary Least Squares variables selected as significant in yellow), Chapter I.:

Mixed Reporting Model:				**Simple Reporting Model:**			
Variable	Estimate	SE	P-value	Variable	Estimate	SE	P-value
Raise/manage sheep in addition to cattle	-0.375	0.202	0.066	Raise/manage sheep in addition to cattle	-0.351	0.195	0.075
Perceived probability of risk (worry)	0.083	0.064	0.201	Perceived probability of risk (worry)	0.105	0.062	0.094
Attitude	0.044	0.108	0.682	Attitude	0.031	0.100	0.754
Belief about utility	0.109	0.069	0.117	Belief about utility	0.099	0.070	0.161
Personal norm	0.122	0.079	0.124	Personal norm	0.142	0.075	0.059
Trust in the reporting process	0.063	0.063	0.319	Trust in the reporting process	0.078	0.062	0.211
Injunctive norm	0.021	0.061	0.736	Injunctive norm	0.035	0.060	0.564
Descriptive norm	0.287	0.087	0.001	Descriptive norm	0.290	0.086	0.001
Attitude compensation	0.069	0.087	0.429	Perceived risk severity	-0.087	0.051	0.091
Perceived risk severity	-0.084	0.053	0.113	Past experience with risk	-0.587	0.290	0.045
Past experience with risk	-0.644	0.323	0.048	Age	0.800	0.270	0.004
Age	0.934	0.327	0.005				

Mixed Compensation Model:			
Variable	Estimate	SE	P-value
California resident	0.829	0.501	0.101
Idaho resident	0.246	0.620	0.692
Montana resident	1.057	0.487	0.032
New Mexico resident	1.358	0.540	0.013
Oregon resident	1.052	0.559	0.063
Wyoming resident	0.283	0.498	0.571
Colorado resident	1.504	0.512	0.004
Perceived probability of risk (worry)	0.055	0.069	0.426
Belief about utility	0.085	0.073	0.248
Personal norm	0.156	0.080	0.054
Trust in the reporting process	0.014	0.063	0.819
Trust in State agencies	0.138	0.051	0.008
Injunctive norm Reporting	0.063	0.075	0.399
Attitude	0.205	0.889	0.023
Perceived risk severity	-0.161	0.059	0.007
Injunctive norm	-0.020	0.091	0.829
Descriptive norm	0.286	0.089	0.002
Age	-0.238	0.118	0.046
Attitude reporting	1.433	0.952	0.135

Simple Compensation Model:			
Variable	Estimate	SE	P-value
California resident	0.749	0.503	0.139
Idaho resident	0.241	0.634	0.704
Montana resident	0.967	0.494	0.053
New Mexico resident	1.238	0.549	0.026
Oregon resident	0.841	0.555	0.133
Wyoming resident	0.222	0.504	0.661
Colorado resident	1.450	0.520	0.006
Perceived probability of risk (worry)	0.069	0.071	0.332
Trust in the reporting process	0.060	0.062	0.333
Trust in Federal agencies	-0.108	0.064	0.093
Trust in State agencies	0.240	0.065	0.001
Attitude	0.235	0.090	0.011
Perceived risk severity	-0.147	0.060	0.015
Injunctive norm	0.062	0.075	0.413
Descriptive norm	0.227	0.091	0.014
Age	-0.209	0.123	0.091

5 Payment Option Descriptions for the Discrete Choice Question, Chapter II. (as presented in survey):

We are interested in getting your perspective on what an ideal producer support program would look like for producers operating on landscapes with depredating wolves. The following question will ask you to choose between five different programs. Each program has three components: a payment option for direct losses, a habitat lease option, and a cost share option. A participant in any of the five programs can take advantage of all, some, or none of the three payment options.

Please review the following details on each payment option, and then select which compensation program you would most prefer to participate in.

Payment Options:

1. Payment for Direct Losses

Similar to traditional depredation compensation programs, livestock depredations that are located, confirmed by the required personnel, and submitted for compensation can receive a fair market value payment per depredated animal. This payment option may or may not include a multiplier for compensation above the fair market value to account for depredated livestock never found. For example, at a multiplier of 3, each located and confirmed wolf depredation will be paid at 3-times the fair market value for one animal.

2. Habitat Lease that Does Not Displace Livestock

An annual payment made to landowners similar to the Conservation Reserve Program (CRP Grasslands), which pays landowners and operators to protect grasslands, including rangelands, pasturelands, and certain other lands while maintaining the areas as grazing lands. This habitat lease option would pay agricultural producers a dollar amount per acre for operating on landscapes with wolves. Participation in the habitat lease would require an initial biodiversity evaluation of lands. Livestock producers operating on both private and/or public lands qualify to participate.

3. Cost Share Program for Wolf Conflict Prevention Tools

A cost-share program for voluntary implementation of proactive conflict prevention and/or non-lethal management tools. As participants, landowners will be provided both financial and technical assistance in the form of equipment and/or services (for example installing fencing). These resources will be paid for by a shared pool of investments funded by NGO's, government agencies, and/or producers. Producer contributions may be in-kind, (labor, materials, etc.) or cash.

6 Data Analysis Steps for Regressions, Chapter I.:

First, I cleaned my data by removing any non-livestock producer responses, responses from producers who did not fill out more than the first question, or responses from states without confirmed wolf populations.

Next, I coded my qualitative responses using the following protocol: since these responses were not included in any regression analyses, I read through each response and created a coded list of generalized categories that each response fit into. These varied across qualitative questions as the number of categories directly reflected the variety of responses to each question (see Section X for qualitative question codes). This coding step allowed me to analyze the frequency of different kinds of responses.

Next, I recoded/standardized my complete and incomplete survey questions to be in numerical order (some were altered during survey creation in Qualtrics – see codebook).

Next, I organized my completed response questions into five separate excel sheets: Reporting Regression Questions, Compensation Regression Questions, Descriptive Statistics Questions, Chapter Two Data Questions, and WLA Data Questions.

I then organized my incomplete responses into similar categories, removing any responses without the appropriate response variable.

For my incomplete response regression datasets (Reporting and Compensation), I removed any response with 30% or more item/question non-response specific to the number or questions associated with each regression.

I then added the remaining incomplete data to my four complete response datasets for the following N values for each regression: Reporting Regression – N = 130, (127 with TPB) and Compensation Regression – N = 128 for with and without TPB (Descriptive Statistics questions, Chapter Two questions, and WLA Data questions will be organized and reported based on each question since these responses will not be used for regressions).

Next I simplified Q2 by deleting the "goat" and "other" options, and simplified Q4 by creating a "Y/N" option for "public" only, assuming all other grazing was on private.

Then I reverse coded the appropriate questions – Q14-15, 17, 21-24, 30-31, 40-41, 45, and 47.

Next, I used the *glmnet* package in R to run correlations on continuous variables, impute the mean for missing responses, and run the four Lasso regressions.

7 R-Code, Chapter I.:

```r
#---------------------------------------------------------------
# Depredation Reporting and Compensation Survey Regressions
# Rae Nickerson, 2021, CCC Funding, CSU
#--------------------------------------------------------------#

# Load libraries
library(ggplot2)
library(tidyverse)
library(dplyr)
library(mice)
library(car)
library(rcompanion)
library(glmnet)
library(GGally)
library(jtools)
library(QuantPsyc)
library(modeest)
library(imputeMissings)
library(miceadds)
library(naniar)
library(remotes)
library(gglasso)

# Code to replace the ck37r package (error):
impute_missing_values <- function(data, type = "standard", add_indicators = TRUE,
                                  prefix = "miss_", skip_vars = NULL, all_vars = FALSE,
                                  remove_constant = TRUE, remove_collinear = TRUE, values = NULL,
                                  h2o_glrm = NULL, glrm_k = 10L, verbose = FALSE)
{
  missing_indicators = NULL
  new_data = data
  non_skipped_vars = !colnames(data) %in% skip_vars
  results = list(type = type, add_indicators = add_indicators,
                 skip_vars = skip_vars, prefix = prefix)
  any_nas = which(sapply(colnames(data), function(col) !col %in%
                           skip_vars && anyNA(data[[col]])))
  if (verbose) {
    cat("Found", length(any_nas), "variables with NAs.\n")
  }
  if (type == "standard") {
    if (verbose) {
      cat("Running standard imputation.\n")
    }
    impute_values = vector("list", sum(non_skipped_vars))
    names(impute_values) = colnames(data[non_skipped_vars])
    if (all_vars) {
      loop_over = which(non_skipped_vars)
      names(loop_over) = colnames(data)[non_skipped_vars]
    }
    else {
      loop_over = any_nas
    }
    sum_nas = sapply(loop_over, function(col_i) sum(is.na(data[[col_i]])))
    col_classes = sapply(loop_over, function(col_i) class(data[[col_i]]))
    for (i in loop_over) {
      colname = names(loop_over)[loop_over == i]
      nas = sum_nas[colname]
      col_class = col_classes[colname]
```

```
    if (verbose) {
      cat("Imputing", colname, paste0("(",
                                      i, " ", col_class, ")"), "with",
          prettyNum(nas, big.mark = ","), "NAs.")
    }
    if (colname %in% names(values)) {
      impute_value = values[[colname]]
      if (verbose) {
        cat(" Pre-filled.")
      }
    }
    else if (col_class %in% c("factor")) {
      impute_value = Mode(data[[i]], exclude_na = TRUE)[1]
    }
    else if (col_class %in% c("integer", "numeric",
                              "logical", "labelled", "integer64")) {
      impute_value = median(data[[i]], na.rm = TRUE)
    }
    else {
      warning(paste(colname, "should be numeric or factor type. But its class is",
                    col_class))
    }
    if (verbose) {
      cat(" Impute value:", impute_value, "\n")
    }
    impute_values[[colname]] = impute_value
    if (nas == nrow(data)) {
      if (verbose) {
        cat("Note: cannot impute", colname, "because all values are NA.\n")
      }
      next
    }
    else if (nas == 0) {
      next
    }
    else {
      new_data[is.na(data[[i]]), i] = impute_value
    }
  }
  if (!all_vars) {
    impute_values = impute_values[names(any_nas)]
  }
  results$impute_values = impute_values
}
else if (type == "knn") {
  if (verbose) {
    cat("Running knn imputation. NOTE: this will standardize your data!\n")
  }
  if (!"RANN" %in% installed.packages()) {
    stop("knn imputation requires the RANN package. Please run install.packages(\"RANN\")")
  }
  impute_info = caret::preProcess(new_data, method = c("knnImpute"))
  new_data = predict(impute_info, new_data)
  results$impute_info = impute_info
}
else if (type == "glrm") {
  if (verbose) {
    cat("Running glrm imputation via h2o.\n")
  }
  capture.output({
```

```
      h2o::h2o.init(nthreads = -1)
    }, split = verbose)
    capture.output({
      df_h2o = h2o::as.h2o(new_data[, !names(new_data) %in%
                                      skip_vars])
    }, split = verbose)
    if (is.null(h2o_glrm)) {
      capture.output({
        model_glrm = h2o::h2o.glrm(training_frame = df_h2o,
                                   k = min(ncol(df_h2o), glrm_k), loss = "Quadratic",
                                   init = "SVD", svd_method = "GramSVD",
                                   regularization_x = "None", regularization_y = "None",
                                   min_step_size = 1e-06, max_iterations = 1000)
      }, split = verbose)
    }
    else {
      model_glrm = h2o_glrm
    }
    capture.output({
      imp_h2o = predict(model_glrm, df_h2o)
    }, split = verbose)
    results$h2o_glrm = model_glrm
    capture.output({
      glrm_data = as.data.frame(imp_h2o)
    }, split = verbose)
    names(glrm_data) = setdiff(names(data), skip_vars)
    for (colname_i in names(any_nas)) {
      missing_val = is.na(new_data[[colname_i]])
      new_data[missing_val, colname_i] = glrm_data[missing_val,
                                                   colname_i]
    }
  }
  if (add_indicators) {
    if (length(any_nas) > 0L) {
      if (verbose) {
        cat("Generating missingness indicators.\n")
      }
      missing_indicators = missingness_indicators(data[,
                                                       names(any_nas), drop = FALSE], prefix =
prefix,
                                                  remove_constant = remove_constant,
remove_collinear = remove_collinear,
                                                  verbose = verbose)
      if (verbose) {
        cat(paste0("Indicators added (", ncol(missing_indicators),
                   "):"), paste(colnames(missing_indicators),
                                collapse = ", "), "\n")
      }
      results$indicators_added = colnames(missing_indicators)
      new_data = cbind(new_data, missing_indicators)
    }
  }
  results$data = new_data
  results
}

missingness_indicators<-function (data, prefix = "miss_", remove_constant = TRUE,
                                  remove_collinear = TRUE, skip_vars = c(), verbose = FALSE){
  any_nas = which(sapply(data[, !colnames(data) %in% skip_vars,
                              drop = FALSE], function(col) anyNA(col)))
```

```
  if (verbose) {
    cat("Generating", length(any_nas), "missingness indicators.\n")
  }
  indicators = 1L * is.na(data[, names(any_nas), drop = FALSE])
  if (length(any_nas) > 0) {
    colnames(indicators) = paste0(prefix, names(any_nas))
  }
  if (remove_constant) {
    col_means = colMeans(indicators)
    if (verbose) {
      num_removed = sum(col_means %in% c(0, 1))
      if (num_removed > 0) {
        cat("Removing", num_removed, "indicators that are constant.\n")
      }
    }
    indicators = indicators[, !col_means %in% c(0, 1), drop = FALSE]
  }
  if (remove_collinear) {
    if (verbose) {
      cat("Checking for collinearity of indicators.\n")
    }
    linear_combos = caret::findLinearCombos(indicators)
    remove_columns = linear_combos$remove
    if (length(linear_combos$remove) > 0L) {
      if (verbose) {
        cat("Removing", length(linear_combos$remove),
            "indicators due to collinearity:\n")
        cat(paste0(colnames(indicators)[linear_combos$remove],
                   collapse = ", "), "\n")
      }
      indicators = indicators[, -linear_combos$remove,
                              drop = FALSE]
    }
  }
  if (verbose) {
    cat("Final number of indicators:", ncol(indicators),
        "\n")
  }
  return(indicators)
}

#-----------------------------------------#
# Future Reporting + C TPB
#-----------------------------------------#

# Upload excel datasheet using "import dataset" or read in data
survey_rtpb <- read.csv("/Users/rachaelnickerson/Desktop/Data_May21/Reporting_TPB_final_wDV.csv",
 header = TRUE, na.strings = c(NA,"NA", ""))

# Clean up variable names
colnames(survey_rtpb) <- gsub("...CON...N","",colnames(survey_rtpb))
colnames(survey_rtpb) <- gsub("...CAT...N","",colnames(survey_rtpb))
colnames(survey_rtpb) <- gsub("...CON...R","",colnames(survey_rtpb))
colnames(survey_rtpb) <- gsub("...CAT...R","",colnames(survey_rtpb))
colnames(survey_rtpb) <- gsub("ï..","",colnames(survey_rtpb))
colnames(survey_rtpb)

# Label categorical variables as factors types
survey_rtpb$Cattle = as.factor(survey_rtpb$Cattle)
survey_rtpb$Sheep = as.factor(survey_rtpb$Sheep)
```

```
survey_rtpb$PrivateLand = as.factor(survey_rtpb$PrivateLand)
survey_rtpb$State <- as.factor(survey_rtpb$State)
survey_rtpb$Dep <- as.factor(survey_rtpb$Dep)
survey_rtpb$Report <- as.factor(survey_rtpb$Report)
survey_rtpb$Nonlethals <- as.factor(survey_rtpb$Nonlethals)
survey_rtpb$RRecord <- as.integer(survey_rtpb$RRecord)
survey_rtpb$Comp <- as.factor(survey_rtpb$Comp)
survey_rtpb$Gender <- as.factor(survey_rtpb$Gender)

# Check that all variables are coded correctly
str(survey_rtpb)

# Recode all -99s as missing
#recode factors:
survey_rtpb[survey_rtpb=="-99"] <- NA
#recode numeric:
survey_rtpb[survey_rtpb==-99] <- NA
survey_rtpb <- droplevels(survey_rtpb) #drop -99 factor levels
str(survey_rtpb)

# Remove categorical variables and DV to run correlation matrix:
survey.cor <- survey_rtpb
survey.cor$Cattle <- NULL
survey.cor$Sheep <- NULL
survey.cor$PrivateLand <- NULL
survey.cor$State <- NULL
survey.cor$Dep <- NULL
survey.cor$Report <- NULL
survey.cor$Nonlethals <- NULL
survey.cor$Comp <- NULL
survey.cor$Gender <- NULL
survey.cor$FR <- NULL

# Run matrix:
cor(x = as.matrix(survey.cor), method = "pearson", use = "pairwise.complete.obs")

# Save the data frame as another object so that we can use the original data frame for multiple
 imputation
survey_rtpb_or <- survey_rtpb

# Remove past compensation behavior variable (since have TPB comp here)
survey_rtpb$Comp <- NULL
# Remove past reporting behavior variable:
survey_rtpb$Report <- NULL
# Remove nonlethals, and correlated variable
survey_rtpb$CDifficult <- NULL
survey_rtpb$CTime <- NULL
survey_rtpb$Nonlethals <- NULL

# Code to use the "mode" function:
  Mode<-function (x, exclude_na = TRUE){
    ux = unique(x)
    if (exclude_na) {
      ux = setdiff(ux, NA)
    }
    tab = tabulate(match(x, ux))
    ux[tab == max(tab)]
  }

# Check missingness
```

```
miss_var_summary(survey_rtpb)
miss_var_table(survey_rtpb)
table(survey_rtpb$Dep)


# Check how much a complete case analysis would drop
sum(complete.cases(survey_rtpb))

# Check out the pattern of missing data
p_missing <- unlist(lapply(survey_rtpb, function(x) sum(is.na(x))))/nrow(survey_rtpb)
sort(p_missing[p_missing > 0], decreasing = TRUE)

# Median/mode impute missing data: (this function adds an indicator variables "miss_X", etc.,
 denoting values that were imputed for the X variable)
df = impute_missing_values(survey_rtpb)$data

#-----------------------------------------
# Analysis #1: Run lasso regression on median imputed data
#-----------------------------------------

df2 <-df
# Add a "lev" to the end of variables so when converted to indicators can see: "original
 variable_factor level" in the variable name
colnames(df2) <- paste0(colnames(df),"lev")

xmatrix = model.matrix(lm(FRlev ~ ., data = df2))
y_vector = df2$FR

set.seed(20201009)

# Note alpha=1 to specifically use LASSO
lassofit = cv.glmnet(xmatrix, y_vector, alpha = 1)
find_coef = coef(lassofit, s=lassofit$lambda.min)
find_coef

# Convert to a dataframe
lasso_coef= data.frame(var=rownames(find_coef), coef=find_coef[,1])
lasso_coef

#-----------------------------------------
# Analysis #2: Run linear regression on lasso-selected variables (median imputed dataset)
#-----------------------------------------

# Select non-zero coefficients for OLS regression analysis
selected_vars <- lasso_coef %>% filter(coef!=0, var!="(Intercept)")
selected_vars <- selected_vars$var

# Select the original variable names for regression analysis so all factor levels are included
 (right now, they are indicator variables)
selected_vars <- unique(str_split(selected_vars,"lev", simplify = T)[,1])

# Call in the imputed dataset of selected variables
df_select <- df %>% subset(., select=c("FR",selected_vars)) %>% as.data.frame()

# Add back in spaces so factor levels are interpretable
colnames(df_select) <- paste0(colnames(df_select),"_")

# Run regression on imputed data
res_imp <- lm(FR_~., data=df_select)
summary(res_imp)
```

```
#--------------------------------------------------------------#
# Future Reporting
#--------------------------------------------------------------#

# Delete everything
rm(list=ls())

# Code to replace the ck37r package (error):
impute_missing_values <- function(data, type = "standard", add_indicators = TRUE,
                                  prefix = "miss_", skip_vars = NULL, all_vars = FALSE,
                                  remove_constant = TRUE, remove_collinear = TRUE, values = NULL,
                                  h2o_glrm = NULL, glrm_k = 10L, verbose = FALSE)
{
  missing_indicators = NULL
  new_data = data
  non_skipped_vars = !colnames(data) %in% skip_vars
  results = list(type = type, add_indicators = add_indicators,
                 skip_vars = skip_vars, prefix = prefix)
  any_nas = which(sapply(colnames(data), function(col) !col %in%
                           skip_vars && anyNA(data[[col]])))
  if (verbose) {
    cat("Found", length(any_nas), "variables with NAs.\n")
  }
  if (type == "standard") {
    if (verbose) {
      cat("Running standard imputation.\n")
    }
    impute_values = vector("list", sum(non_skipped_vars))
    names(impute_values) = colnames(data[non_skipped_vars])
    if (all_vars) {
      loop_over = which(non_skipped_vars)
      names(loop_over) = colnames(data)[non_skipped_vars]
    }
    else {
      loop_over = any_nas
    }
    sum_nas = sapply(loop_over, function(col_i) sum(is.na(data[[col_i]])))
    col_classes = sapply(loop_over, function(col_i) class(data[[col_i]]))
    for (i in loop_over) {
      colname = names(loop_over)[loop_over == i]
      nas = sum_nas[colname]
      col_class = col_classes[colname]
      if (verbose) {
        cat("Imputing", colname, paste0("(",
                                        i, " ", col_class, ")"), "with",
            prettyNum(nas, big.mark = ","), "NAs.")
      }
      if (colname %in% names(values)) {
        impute_value = values[[colname]]
        if (verbose) {
          cat(" Pre-filled.")
        }
      }
      else if (col_class %in% c("factor")) {
        impute_value = Mode(data[[i]], exclude_na = TRUE)[1]
      }
      else if (col_class %in% c("integer", "numeric",
                                "logical", "labelled", "integer64")) {
        impute_value = median(data[[i]], na.rm = TRUE)
```

```
    }
    else {
      warning(paste(colname, "should be numeric or factor type. But its class is",
                    col_class))
    }
    if (verbose) {
      cat(" Impute value:", impute_value, "\n")
    }
    impute_values[[colname]] = impute_value
    if (nas == nrow(data)) {
      if (verbose) {
        cat("Note: cannot impute", colname, "because all values are NA.\n")
      }
      next
    }
    else if (nas == 0) {
      next
    }
    else {
      new_data[is.na(data[[i]]), i] = impute_value
    }
  }
  if (!all_vars) {
    impute_values = impute_values[names(any_nas)]
  }
  results$impute_values = impute_values
}
else if (type == "knn") {
  if (verbose) {
    cat("Running knn imputation. NOTE: this will standardize your data!\n")
  }
  if (!"RANN" %in% installed.packages()) {
    stop("knn imputation requires the RANN package. Please run install.packages(\"RANN\")")
  }
  impute_info = caret::preProcess(new_data, method = c("knnImpute"))
  new_data = predict(impute_info, new_data)
  results$impute_info = impute_info
}
else if (type == "glrm") {
  if (verbose) {
    cat("Running glrm imputation via h2o.\n")
  }
  capture.output({
    h2o::h2o.init(nthreads = -1)
  }, split = verbose)
  capture.output({
    df_h2o = h2o::as.h2o(new_data[, !names(new_data) %in%
                                  skip_vars])
  }, split = verbose)
  if (is.null(h2o_glrm)) {
    capture.output({
      model_glrm = h2o::h2o.glrm(training_frame = df_h2o,
                            k = min(ncol(df_h2o), glrm_k), loss = "Quadratic",
                            init = "SVD", svd_method = "GramSVD",
                            regularization_x = "None", regularization_y = "None",
                            min_step_size = 1e-06, max_iterations = 1000)
    }, split = verbose)
  }
  else {
    model_glrm = h2o_glrm
```

```
    }
    capture.output({
      imp_h2o = predict(model_glrm, df_h2o)
    }, split = verbose)
    results$h2o_glrm = model_glrm
    capture.output({
      glrm_data = as.data.frame(imp_h2o)
    }, split = verbose)
    names(glrm_data) = setdiff(names(data), skip_vars)
    for (colname_i in names(any_nas)) {
      missing_val = is.na(new_data[[colname_i]])
      new_data[missing_val, colname_i] = glrm_data[missing_val,
                                                    colname_i]
    }
  }
  if (add_indicators) {
    if (length(any_nas) > 0L) {
      if (verbose) {
        cat("Generating missingness indicators.\n")
      }
      missing_indicators = missingness_indicators(data[,
                                                        names(any_nas), drop = FALSE], prefix =
 prefix,
                                                   remove_constant = remove_constant,
 remove_collinear = remove_collinear,
                                                   verbose = verbose)
      if (verbose) {
        cat(paste0("Indicators added (", ncol(missing_indicators),
                   "):"), paste(colnames(missing_indicators),
                                collapse = ", "), "\n")
      }
      results$indicators_added = colnames(missing_indicators)
      new_data = cbind(new_data, missing_indicators)
    }
  }
  results$data = new_data
  results
}

missingness_indicators<-function (data, prefix = "miss_", remove_constant = TRUE,
                                  remove_collinear = TRUE, skip_vars = c(), verbose = FALSE){
  any_nas = which(sapply(data[, !colnames(data) %in% skip_vars,
                              drop = FALSE], function(col) anyNA(col)))
  if (verbose) {
    cat("Generating", length(any_nas), "missingness indicators.\n")
  }
  indicators = 1L * is.na(data[, names(any_nas), drop = FALSE])
  if (length(any_nas) > 0) {
    colnames(indicators) = paste0(prefix, names(any_nas))
  }
  if (remove_constant) {
    col_means = colMeans(indicators)
    if (verbose) {
      num_removed = sum(col_means %in% c(0, 1))
      if (num_removed > 0) {
        cat("Removing", num_removed, "indicators that are constant.\n")
      }
    }
    indicators = indicators[, !col_means %in% c(0, 1), drop = FALSE]
  }
```

```
  if (remove_collinear) {
    if (verbose) {
      cat("Checking for collinearity of indicators.\n")
    }
    linear_combos = caret::findLinearCombos(indicators)
    remove_columns = linear_combos$remove
    if (length(linear_combos$remove) > 0L) {
      if (verbose) {
        cat("Removing", length(linear_combos$remove),
            "indicators due to collinearity:\n")
        cat(paste0(colnames(indicators)[linear_combos$remove],
                   collapse = ", "), "\n")
      }
      indicators = indicators[, -linear_combos$remove,
                              drop = FALSE]
    }
  }
  if (verbose) {
    cat("Final number of indicators:", ncol(indicators),
        "\n")
  }
  return(indicators)
}

# Upload excel datasheet using "import dataset" or read in data
survey_r <- read.csv("/Users/rachaelnickerson/Desktop/Data_May21/Reporting_final_wDV.csv", header
 = TRUE, na.strings = c(NA,"NA", ""))

# Clean up variable names
colnames(survey_r) <- gsub("...CON...N","",colnames(survey_r))
colnames(survey_r) <- gsub("...CAT...N","",colnames(survey_r))
colnames(survey_r) <- gsub("...CON...R","",colnames(survey_r))
colnames(survey_r) <- gsub("...CAT...R","",colnames(survey_r))
colnames(survey_r) <- gsub("ï..","",colnames(survey_r))
colnames(survey_r)

# Label categorical variables as factors types
survey_r$Cattle = as.factor(survey_r$Cattle)
survey_r$Sheep = as.factor(survey_r$Sheep)
survey_r$PrivateLand = as.factor(survey_r$PrivateLand)
survey_r$State <- as.factor(survey_r$State)
survey_r$Dep <- as.factor(survey_r$Dep)
survey_r$Report <- as.factor(survey_r$Report)
survey_r$Nonlethals <- as.factor(survey_r$Nonlethals)
survey_r$RRecord <- as.integer(survey_r$RRecord)
survey_r$Comp <- as.factor(survey_r$Comp)
survey_r$Gender <- as.factor(survey_r$Gender)

# Check that all variables are coded correctly
str(survey_r)

# Recode all -99s as missing
# recode factors:
survey_r[survey_r=="-99"] <- NA
#recode numeric:
survey_r[survey_r==-99] <- NA
survey_r <- droplevels(survey_r) #drop -99 factor levels
str(survey_r)

# Remove categorical variables to run correlation matrix:
```

```
survey.cor <- survey_r
survey.cor$Cattle <- NULL
survey.cor$Sheep <- NULL
survey.cor$PrivateLand <- NULL
survey.cor$State <- NULL
survey.cor$Dep <- NULL
survey.cor$Report <- NULL
survey.cor$Nonlethals <- NULL
survey.cor$Comp <- NULL
survey.cor$Gender <- NULL
survey.cor$FR <- NULL

# Run matrix:
cor(x = as.matrix(survey.cor), method = "pearson", use = "pairwise.complete.obs")


# Save the data frame as another object so that we can use the original data frame for multiple
 imputation
survey_r_or <- survey_r

# Remove past reporting and compensation behavior variables because of correlation and skip
 logic:
survey_r$Report <- NULL
survey_r$Comp <- NULL
# Remove nonlethals
survey_r$Nonlethals <- NULL

# Code to use the "mode" function:
Mode<-function (x, exclude_na = TRUE){
  ux = unique(x)
  if (exclude_na) {
    ux = setdiff(ux, NA)
  }
  tab = tabulate(match(x, ux))
  ux[tab == max(tab)]
}

# Check missingness
miss_var_table(survey_r)
table(survey_r$Dep)

# Check how much a complete case analysis would drop
sum(complete.cases(survey_r))

# Check out the pattern of missing data
p_missing <- unlist(lapply(survey_r, function(x) sum(is.na(x))))/nrow(survey_r)
sort(p_missing[p_missing > 0], decreasing = TRUE)

# Median/mode impute missing data: (this function adds an indicator variables "miss_X", etc.,
 denoting values that were imputed for the X variable)
df = impute_missing_values(survey_r)$data

#-----------------------------------------
# Analysis #1: Run lasso regression on median imputed data
#-----------------------------------------

df2 <-df
# Add a "lev" to the end of variables so when converted to indicators can see: "original
 variable_factor level" in the variable name
colnames(df2) <- paste0(colnames(df),"lev")
```

```
xmatrix = model.matrix(lm(FRlev ~ ., data = df2))
y_vector = df2$FR

set.seed(20201009)

# Note alpha=1 to specifically use LASSO
lassofit = cv.glmnet(xmatrix, y_vector, alpha = 1)
find_coef = coef(lassofit, s=lassofit$lambda.min)
find_coef

# Convert to a dataframe
lasso_coef= data.frame(var=rownames(find_coef), coef=find_coef[,1])
lasso_coef


#-----------------------------------------
# Analysis #2: Run linear regression on lasso-selected variables (median imputed dataset)
#-----------------------------------------

# Select non-zero coefficients for OLS regression analysis
selected_vars <- lasso_coef %>% filter(coef!=0, var!="(Intercept)")
selected_vars <- selected_vars$var

# Select the original variable names for regression analysis so all factor levels are included
 (right now, they are indicator variables)
selected_vars <- unique(str_split(selected_vars,"lev", simplify = T)[,1])

# Call in the imputed dataset of selected variables
df_select <- df %>% subset(., select=c("FR",selected_vars)) %>% as.data.frame()

# Add back in spaces so factor levels are interpretable
colnames(df_select) <- paste0(colnames(df_select),"_")

# Run regression on imputed data
res_imp <- lm(FR_~., data=df_select)
summary(res_imp)


#------------------------------------------------------------------------------------------#
# Future Compensation + R TPB
#------------------------------------------------------------------------------------------#

# Delete everything
rm(list=ls())

# Code to replace the ck37r package (error):
impute_missing_values <- function(data, type = "standard", add_indicators = TRUE,
                                  prefix = "miss_", skip_vars = NULL, all_vars = FALSE,
                                  remove_constant = TRUE, remove_collinear = TRUE, values = NULL,
                                  h2o_glrm = NULL, glrm_k = 10L, verbose = FALSE)
{
  missing_indicators = NULL
  new_data = data
  non_skipped_vars = !colnames(data) %in% skip_vars
  results = list(type = type, add_indicators = add_indicators,
                 skip_vars = skip_vars, prefix = prefix)
  any_nas = which(sapply(colnames(data), function(col) !col %in%
                           skip_vars && anyNA(data[[col]])))
  if (verbose) {
```

```
    cat("Found", length(any_nas), "variables with NAs.\n")
  }
  if (type == "standard") {
    if (verbose) {
      cat("Running standard imputation.\n")
    }
    impute_values = vector("list", sum(non_skipped_vars))
    names(impute_values) = colnames(data[non_skipped_vars])
    if (all_vars) {
      loop_over = which(non_skipped_vars)
      names(loop_over) = colnames(data)[non_skipped_vars]
    }
    else {
      loop_over = any_nas
    }
    sum_nas = sapply(loop_over, function(col_i) sum(is.na(data[[col_i]])))
    col_classes = sapply(loop_over, function(col_i) class(data[[col_i]]))
    for (i in loop_over) {
      colname = names(loop_over)[loop_over == i]
      nas = sum_nas[colname]
      col_class = col_classes[colname]
      if (verbose) {
        cat("Imputing", colname, paste0("(",
                                        i, " ", col_class, ")"), "with",
            prettyNum(nas, big.mark = ","), "NAs.")
      }
      if (colname %in% names(values)) {
        impute_value = values[[colname]]
        if (verbose) {
          cat(" Pre-filled.")
        }
      }
      else if (col_class %in% c("factor")) {
        impute_value = Mode(data[[i]], exclude_na = TRUE)[1]
      }
      else if (col_class %in% c("integer", "numeric",
                                "logical", "labelled", "integer64")) {
        impute_value = median(data[[i]], na.rm = TRUE)
      }
      else {
        warning(paste(colname, "should be numeric or factor type. But its class is",
                      col_class))
      }
      if (verbose) {
        cat(" Impute value:", impute_value, "\n")
      }
      impute_values[[colname]] = impute_value
      if (nas == nrow(data)) {
        if (verbose) {
          cat("Note: cannot impute", colname, "because all values are NA.\n")
        }
        next
      }
      else if (nas == 0) {
        next
      }
      else {
        new_data[is.na(data[[i]]), i] = impute_value
      }
    }
```

```
  if (!all_vars) {
    impute_values = impute_values[names(any_nas)]
  }
  results$impute_values = impute_values
}
else if (type == "knn") {
  if (verbose) {
    cat("Running knn imputation. NOTE: this will standardize your data!\n")
  }
  if (!"RANN" %in% installed.packages()) {
    stop("knn imputation requires the RANN package. Please run install.packages(\"RANN\")")
  }
  impute_info = caret::preProcess(new_data, method = c("knnImpute"))
  new_data = predict(impute_info, new_data)
  results$impute_info = impute_info
}
else if (type == "glrm") {
  if (verbose) {
    cat("Running glrm imputation via h2o.\n")
  }
  capture.output({
    h2o::h2o.init(nthreads = -1)
  }, split = verbose)
  capture.output({
    df_h2o = h2o::as.h2o(new_data[, !names(new_data) %in%
                                    skip_vars])
  }, split = verbose)
  if (is.null(h2o_glrm)) {
    capture.output({
      model_glrm = h2o::h2o.glrm(training_frame = df_h2o,
                                 k = min(ncol(df_h2o), glrm_k), loss = "Quadratic",
                                 init = "SVD", svd_method = "GramSVD",
                                 regularization_x = "None", regularization_y = "None",
                                 min_step_size = 1e-06, max_iterations = 1000)
    }, split = verbose)
  }
  else {
    model_glrm = h2o_glrm
  }
  capture.output({
    imp_h2o = predict(model_glrm, df_h2o)
  }, split = verbose)
  results$h2o_glrm = model_glrm
  capture.output({
    glrm_data = as.data.frame(imp_h2o)
  }, split = verbose)
  names(glrm_data) = setdiff(names(data), skip_vars)
  for (colname_i in names(any_nas)) {
    missing_val = is.na(new_data[[colname_i]])
    new_data[missing_val, colname_i] = glrm_data[missing_val,
                                                 colname_i]
  }
}
if (add_indicators) {
  if (length(any_nas) > 0L) {
    if (verbose) {
      cat("Generating missingness indicators.\n")
    }
    missing_indicators = missingness_indicators(data[,
```

```
                                                     names(any_nas), drop = FALSE], prefix =
prefix,
                                                     remove_constant = remove_constant,
remove_collinear = remove_collinear,
                                                     verbose = verbose)
      if (verbose) {
        cat(paste0("Indicators added (", ncol(missing_indicators),
                   "):"), paste(colnames(missing_indicators),
                                collapse = ", "), "\n")
      }
      results$indicators_added = colnames(missing_indicators)
      new_data = cbind(new_data, missing_indicators)
    }
  }
  results$data = new_data
  results
}

missingness_indicators<-function (data, prefix = "miss_", remove_constant = TRUE,
                                  remove_collinear = TRUE, skip_vars = c(), verbose = FALSE){
  any_nas = which(sapply(data[, !colnames(data) %in% skip_vars,
                              drop = FALSE], function(col) anyNA(col)))
  if (verbose) {
    cat("Generating", length(any_nas), "missingness indicators.\n")
  }
  indicators = 1L * is.na(data[, names(any_nas), drop = FALSE])
  if (length(any_nas) > 0) {
    colnames(indicators) = paste0(prefix, names(any_nas))
  }
  if (remove_constant) {
    col_means = colMeans(indicators)
    if (verbose) {
      num_removed = sum(col_means %in% c(0, 1))
      if (num_removed > 0) {
        cat("Removing", num_removed, "indicators that are constant.\n")
      }
    }
    indicators = indicators[, !col_means %in% c(0, 1), drop = FALSE]
  }
  if (remove_collinear) {
    if (verbose) {
      cat("Checking for collinearity of indicators.\n")
    }
    linear_combos = caret::findLinearCombos(indicators)
    remove_columns = linear_combos$remove
    if (length(linear_combos$remove) > 0L) {
      if (verbose) {
        cat("Removing", length(linear_combos$remove),
            "indicators due to collinearity:\n")
        cat(paste0(colnames(indicators)[linear_combos$remove],
                   collapse = ", "), "\n")
      }
      indicators = indicators[, -linear_combos$remove,
                              drop = FALSE]
    }
  }
  if (verbose) {
    cat("Final number of indicators:", ncol(indicators),
        "\n")
  }
```

```
  return(indicators)
}


# Upload excel datasheet using "import dataset" or read in data
survey_ctpb <-
 read.csv("/Users/rachaelnickerson/Desktop/Data_May21/Compensation_TPB_final_wDV.csv", header =
 TRUE, na.strings = c(NA,"NA", ""))

# Clean up variable names
colnames(survey_ctpb) <- gsub("...CON...N","",colnames(survey_ctpb))
colnames(survey_ctpb) <- gsub("...CAT...N","",colnames(survey_ctpb))
colnames(survey_ctpb) <- gsub("...CON...R","",colnames(survey_ctpb))
colnames(survey_ctpb) <- gsub("...CAT...R","",colnames(survey_ctpb))
colnames(survey_ctpb) <- gsub("ï..","",colnames(survey_ctpb))
colnames(survey_ctpb)

# Label categorical variables as factors types
survey_ctpb$Cattle = as.factor(survey_ctpb$Cattle)
survey_ctpb$Sheep = as.factor(survey_ctpb$Sheep)
survey_ctpb$PrivateLand = as.factor(survey_ctpb$PrivateLand)
survey_ctpb$State <- as.factor(survey_ctpb$State)
survey_ctpb$Dep <- as.factor(survey_ctpb$Dep)
survey_ctpb$Report <- as.factor(survey_ctpb$Report)
survey_ctpb$Nonlethals <- as.factor(survey_ctpb$Nonlethals)
survey_ctpb$RRecord <- as.integer(survey_ctpb$RRecord)
survey_ctpb$Comp <- as.factor(survey_ctpb$Comp)
survey_ctpb$Gender <- as.factor(survey_ctpb$Gender)

# Check that all variables are coded correctly
str(survey_ctpb)

# Recode all -99s as missing
#recode factors:
survey_ctpb[survey_ctpb=="-99"] <- NA
#recode numeric:
survey_ctpb[survey_ctpb==-99] <- NA
survey_ctpb <- droplevels(survey_ctpb) #drop -99 factor levels
str(survey_ctpb)

# Remove categorical variables and DV to run correlation matrix:
survey.cor <- survey_ctpb
survey.cor$Cattle <- NULL
survey.cor$Sheep <- NULL
survey.cor$PrivateLand <- NULL
survey.cor$State <- NULL
survey.cor$Dep <- NULL
survey.cor$Report <- NULL
survey.cor$Nonlethals <- NULL
survey.cor$Comp <- NULL
survey.cor$Gender <- NULL
survey.cor$FC <- NULL

# Run matrix:
cor(x = as.matrix(survey.cor), method = "pearson", use = "pairwise.complete.obs")


# Save the data frame as another object so that we can use the original data frame for multiple
 imputation
survey_ctpb_or <- survey_ctpb
```

```
# Remove past compensation behavior variable because of correlation
survey_ctpb$Comp <- NULL
# Remove past reporting behavior variable because have TPB reporting
survey_ctpb$Report <- NULL
# Remove nonlethals, and correlated variable
survey_ctpb$Nonlethals <- NULL
survey_ctpb$CDifficult <- NULL
survey_ctpb$CTime <- NULL

# Code to use the "mode" function:
Mode<-function (x, exclude_na = TRUE){
  ux = unique(x)
  if (exclude_na) {
    ux = setdiff(ux, NA)
  }
  tab = tabulate(match(x, ux))
  ux[tab == max(tab)]
}

# Check missingness
miss_var_table(survey_ctpb)
table(survey_ctpb$Q7)

# Check how much a complete case analysis would drop
sum(complete.cases(survey_ctpb))

# Check out the pattern of missing data
p_missing <- unlist(lapply(survey_ctpb, function(x) sum(is.na(x))))/nrow(survey_ctpb)
sort(p_missing[p_missing > 0], decreasing = TRUE)

# Median/mode impute missing data: (this function adds an indicator variables "miss_X", etc.,
 denoting values that were imputed for the X variable)
df = impute_missing_values(survey_ctpb)$data

#------------------------------------------
# Analysis #1: Run lasso regression on median imputed data
#------------------------------------------

df2 <-df
# Add a "lev" to the end of variables so when converted to indicators can see: "original
 variable_factor level" in the variable name
colnames(df2) <- paste0(colnames(df),"lev")

xmatrix = model.matrix(lm(FClev ~ ., data = df2))
y_vector = df2$FC

set.seed(20201009)

# Note alpha=1 to specifically use LASSO
lassofit = cv.glmnet(xmatrix, y_vector, alpha = 1)
find_coef = coef(lassofit, s=lassofit$lambda.min)
find_coef

# Convert to a dataframe
lasso_coef= data.frame(var=rownames(find_coef), coef=find_coef[,1])
lasso_coef


#------------------------------------------
```

```
# Analysis #2: Run linear regression on lasso-selected variables (median imputed dataset)
#------------------------------------------

# Select non-zero coefficients for OLS regression analysis
selected_vars <- lasso_coef %>% filter(coef!=0, var!="(Intercept)")
selected_vars <- selected_vars$var

# Select the original variable names for regression analysis so all factor levels are included
 (right now, they are indicator variables)
selected_vars <- unique(str_split(selected_vars,"lev", simplify = T)[,1])

# Call in the imputed dataset of selected variables
df_select <- df %>% subset(., select=c("FC",selected_vars)) %>% as.data.frame()

# Add back in spaces so factor levels are interpretable
colnames(df_select) <- paste0(colnames(df_select),"_")

# Run regression on imputed data
res_imp <- lm(FC_~., data=df_select)
summary(res_imp)

#----------------------------------------------------------------------------------#
# Future Compensation
#----------------------------------------------------------------------------------#

# Delete everything
rm(list=ls())

# Code to replace the ck37r package (error):
impute_missing_values <- function(data, type = "standard", add_indicators = TRUE,
                                  prefix = "miss_", skip_vars = NULL, all_vars = FALSE,
                                  remove_constant = TRUE, remove_collinear = TRUE, values = NULL,
                                  h2o_glrm = NULL, glrm_k = 10L, verbose = FALSE)
{
  missing_indicators = NULL
  new_data = data
  non_skipped_vars = !colnames(data) %in% skip_vars
  results = list(type = type, add_indicators = add_indicators,
                 skip_vars = skip_vars, prefix = prefix)
  any_nas = which(sapply(colnames(data), function(col) !col %in%
                           skip_vars && anyNA(data[[col]])))
  if (verbose) {
    cat("Found", length(any_nas), "variables with NAs.\n")
  }
  if (type == "standard") {
    if (verbose) {
      cat("Running standard imputation.\n")
    }
    impute_values = vector("list", sum(non_skipped_vars))
    names(impute_values) = colnames(data[non_skipped_vars])
    if (all_vars) {
      loop_over = which(non_skipped_vars)
      names(loop_over) = colnames(data)[non_skipped_vars]
    }
    else {
      loop_over = any_nas
    }
    sum_nas = sapply(loop_over, function(col_i) sum(is.na(data[[col_i]])))
    col_classes = sapply(loop_over, function(col_i) class(data[[col_i]]))
    for (i in loop_over) {
```

```
    colname = names(loop_over)[loop_over == i]
    nas = sum_nas[colname]
    col_class = col_classes[colname]
    if (verbose) {
      cat("Imputing", colname, paste0("(",
                                      i, " ", col_class, ")"), "with",
          prettyNum(nas, big.mark = ","), "NAs.")
    }
    if (colname %in% names(values)) {
      impute_value = values[[colname]]
      if (verbose) {
        cat(" Pre-filled.")
      }
    }
    else if (col_class %in% c("factor")) {
      impute_value = Mode(data[[i]], exclude_na = TRUE)[1]
    }
    else if (col_class %in% c("integer", "numeric",
                              "logical", "labelled", "integer64")) {
      impute_value = median(data[[i]], na.rm = TRUE)
    }
    else {
      warning(paste(colname, "should be numeric or factor type. But its class is",
                    col_class))
    }
    if (verbose) {
      cat(" Impute value:", impute_value, "\n")
    }
    impute_values[[colname]] = impute_value
    if (nas == nrow(data)) {
      if (verbose) {
        cat("Note: cannot impute", colname, "because all values are NA.\n")
      }
      next
    }
    else if (nas == 0) {
      next
    }
    else {
      new_data[is.na(data[[i]]), i] = impute_value
    }
  }
  if (!all_vars) {
    impute_values = impute_values[names(any_nas)]
  }
  results$impute_values = impute_values
}
else if (type == "knn") {
  if (verbose) {
    cat("Running knn imputation. NOTE: this will standardize your data!\n")
  }
  if (!"RANN" %in% installed.packages()) {
    stop("knn imputation requires the RANN package. Please run install.packages(\"RANN\")")
  }
  impute_info = caret::preProcess(new_data, method = c("knnImpute"))
  new_data = predict(impute_info, new_data)
  results$impute_info = impute_info
}
else if (type == "glrm") {
  if (verbose) {
```

```
      cat("Running glrm imputation via h2o.\n")
    }
    capture.output({
      h2o::h2o.init(nthreads = -1)
    }, split = verbose)
    capture.output({
      df_h2o = h2o::as.h2o(new_data[, !names(new_data) %in%
                                      skip_vars])
    }, split = verbose)
    if (is.null(h2o_glrm)) {
      capture.output({
        model_glrm = h2o::h2o.glrm(training_frame = df_h2o,
                                   k = min(ncol(df_h2o), glrm_k), loss = "Quadratic",
                                   init = "SVD", svd_method = "GramSVD",
                                   regularization_x = "None", regularization_y = "None",
                                   min_step_size = 1e-06, max_iterations = 1000)
      }, split = verbose)
    }
    else {
      model_glrm = h2o_glrm
    }
    capture.output({
      imp_h2o = predict(model_glrm, df_h2o)
    }, split = verbose)
    results$h2o_glrm = model_glrm
    capture.output({
      glrm_data = as.data.frame(imp_h2o)
    }, split = verbose)
    names(glrm_data) = setdiff(names(data), skip_vars)
    for (colname_i in names(any_nas)) {
      missing_val = is.na(new_data[[colname_i]])
      new_data[missing_val, colname_i] = glrm_data[missing_val,
                                                   colname_i]
    }
  }
  if (add_indicators) {
    if (length(any_nas) > 0L) {
      if (verbose) {
        cat("Generating missingness indicators.\n")
      }
      missing_indicators = missingness_indicators(data[,
                                                       names(any_nas), drop = FALSE], prefix =
 prefix,
                                                  remove_constant = remove_constant,
 remove_collinear = remove_collinear,
                                                  verbose = verbose)
      if (verbose) {
        cat(paste0("Indicators added (", ncol(missing_indicators),
                   "):"), paste(colnames(missing_indicators),
                                collapse = ", "), "\n")
      }
      results$indicators_added = colnames(missing_indicators)
      new_data = cbind(new_data, missing_indicators)
    }
  }
  results$data = new_data
  results
}

missingness_indicators<-function (data, prefix = "miss_", remove_constant = TRUE,
```

```
                                remove_collinear = TRUE, skip_vars = c(), verbose = FALSE){
  any_nas = which(sapply(data[, !colnames(data) %in% skip_vars,
                              drop = FALSE], function(col) anyNA(col)))
  if (verbose) {
    cat("Generating", length(any_nas), "missingness indicators.\n")
  }
  indicators = 1L * is.na(data[, names(any_nas), drop = FALSE])
  if (length(any_nas) > 0) {
    colnames(indicators) = paste0(prefix, names(any_nas))
  }
  if (remove_constant) {
    col_means = colMeans(indicators)
    if (verbose) {
      num_removed = sum(col_means %in% c(0, 1))
      if (num_removed > 0) {
        cat("Removing", num_removed, "indicators that are constant.\n")
      }
    }
    indicators = indicators[, !col_means %in% c(0, 1), drop = FALSE]
  }
  if (remove_collinear) {
    if (verbose) {
      cat("Checking for collinearity of indicators.\n")
    }
    linear_combos = caret::findLinearCombos(indicators)
    remove_columns = linear_combos$remove
    if (length(linear_combos$remove) > 0L) {
      if (verbose) {
        cat("Removing", length(linear_combos$remove),
            "indicators due to collinearity:\n")
        cat(paste0(colnames(indicators)[linear_combos$remove],
                   collapse = ", "), "\n")
      }
      indicators = indicators[, -linear_combos$remove,
                              drop = FALSE]
    }
  }
  if (verbose) {
    cat("Final number of indicators:", ncol(indicators),
        "\n")
  }
  return(indicators)
}


# Upload excel datasheet using "import dataset" or read in data
survey_c <- read.csv("/Users/rachaelnickerson/Desktop/Data_May21/Compensation_final_wDV.csv",
 header = TRUE, na.strings = c(NA,"NA", ""))

# Clean up variable names
colnames(survey_c) <- gsub("...CON...N","",colnames(survey_c))
colnames(survey_c) <- gsub("...CAT...N","",colnames(survey_c))
colnames(survey_c) <- gsub("...CON...R","",colnames(survey_c))
colnames(survey_c) <- gsub("...CAT...R","",colnames(survey_c))
colnames(survey_c) <- gsub("ï..","",colnames(survey_c))
colnames(survey_c)

# Label categorical variables as factors types
survey_c$Cattle = as.factor(survey_c$Cattle)
survey_c$Sheep = as.factor(survey_c$Sheep)
```

```
survey_c$PrivateLand = as.factor(survey_c$PrivateLand)
survey_c$State <- as.factor(survey_c$State)
survey_c$Dep <- as.factor(survey_c$Dep)
survey_c$Report <- as.factor(survey_c$Report)
survey_c$Nonlethals <- as.factor(survey_c$Nonlethals)
survey_c$Comp <- as.factor(survey_c$Comp)
survey_c$Gender <- as.factor(survey_c$Gender)

# Check that all variables are coded correctly
str(survey_c)

# Recode all -99s as missing
# recode factors:
survey_c[survey_c=="-99"] <- NA
#recode numeric:
survey_c[survey_c==-99] <- NA
survey_c <- droplevels(survey_c) #drop -99 factor levels
str(survey_c)

# Remove categorical variables and DV to run correlation matrix:
survey.cor <- survey_c
survey.cor$Cattle <- NULL
survey.cor$Sheep <- NULL
survey.cor$PrivateLand <- NULL
survey.cor$State <- NULL
survey.cor$Dep <- NULL
survey.cor$Report <- NULL
survey.cor$Nonlethals <- NULL
survey.cor$Comp <- NULL
survey.cor$Gender <- NULL
survey.cor$FC <- NULL

# Run matrix:
cor(x = as.matrix(survey.cor), method = "pearson", use = "pairwise.complete.obs")


# Save the data frame as another object so that we can use the original data frame for multiple
 imputation
survey_c_or <- survey_c

# Remove past compensation behavior variable for correlation and Reporting for skiplogic
survey_c$Comp <- NULL
# Remove past reporting behavior because of correlation
survey_c$Report <- NULL
# Remove nonlethals and correlated variable
survey_c$Nonlethals <- NULL
survey_c$CDifficult <- NULL
survey_c$CTime <- NULL

# Code to use the "mode" function:
Mode<-function (x, exclude_na = TRUE){
  ux = unique(x)
  if (exclude_na) {
    ux = setdiff(ux, NA)
  }
  tab = tabulate(match(x, ux))
  ux[tab == max(tab)]
}

# Check missingness
```

```
miss_var_table(survey_c)
table(survey_c$Dep)

# Check how much a complete case analysis would drop
sum(complete.cases(survey_c))

# Check out the pattern of missing data
p_missing <- unlist(lapply(survey_c, function(x) sum(is.na(x))))/nrow(survey_c)
sort(p_missing[p_missing > 0], decreasing = TRUE)

# Median/mode impute missing data: (this function adds an indicator variables "miss_X", etc.,
 denoting values that were imputed for the X variable)
df = impute_missing_values(survey_c)$data

#------------------------------------------
# Analysis #1: Run lasso regression on median imputed data
#------------------------------------------

df2 <-df
# Add a "lev" to the end of variables so when converted to indicators can see: "original
 variable_factor level" in the variable name
colnames(df2) <- paste0(colnames(df),"lev")

xmatrix = model.matrix(lm(FClev ~ ., data = df2))
y_vector = df2$FC

set.seed(20201009)

# Note alpha=1 to specifically use LASSO
lassofit = cv.glmnet(xmatrix, y_vector, alpha = 1)
find_coef = coef(lassofit, s=lassofit$lambda.min)
find_coef

# Convert to a dataframe
lasso_coef= data.frame(var=rownames(find_coef), coef=find_coef[,1])
lasso_coef


#------------------------------------------
# Analysis #2: Run linear regression on lasso-selected variables (median imputed dataset)
#------------------------------------------

# Select non-zero coefficients for OLS regression analysis
selected_vars <- lasso_coef %>% filter(coef!=0, var!="(Intercept)")
selected_vars <- selected_vars$var

# Select the original variable names for regression analysis so all factor levels are included
 (right now, they are indicator variables)
selected_vars <- unique(str_split(selected_vars,"lev", simplify = T)[,1])

# Call in the imputed dataset of selected variables
df_select <- df %>% subset(., select=c("FC",selected_vars)) %>% as.data.frame()

# Add back in spaces so factor levels are interpretable
colnames(df_select) <- paste0(colnames(df_select),"_")

# Run regression on imputed data
res_imp <- lm(FC_~., data=df_select)
summary(res_imp)
```