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RESEARCH ARTICLE

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# Success is dependent on effort: Unraveling characteristics of successful deer and elk hunters

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## Abstract

The pursuit of ungulates as game animals, whether for recreation, cultural tradition, or meat, is a dominant activity on public and private lands in North America and much of the world. Strategic regulation of hunting is key for managing game population abundance, age and sex structure, and distribution, with harvest rates a function of both hunter success and participation. Hunter satisfaction is often linked to success and ultimately with hunter recruitment and retention, a growing concern for wildlife agencies. Yet knowledge is lacking about what hunter characteristics or behaviors are linked with success, and how these may differ among common hunt types. We used survey and spatial data from hunters ($n$ = 416) during a 6-year observational study in northeastern Oregon, USA to characterize hunter traits associated with success for 3 hunt types for antlered males: rifle deer (*Odocoileus* spp.), archery elk (*Cervus canadensis*), and rifle elk. We modeled the success for rifle deer and rifle elk hunters using logistic regression models in a Bayesian hierarchical approach. Annual success rates were highly variable, ranging from 4 to 76% for rifle deer and 20 to 56% for rifle elk hunters, and from 0 to 14% for archery elk. Age distributions of hunters were similar across

*Retired

hunt types ($\bar{x}$ = 47.2 years), and male hunters were ~8 times as common as females ($n$ = 370 vs. $n$ = 46, respectively). Success rates for men and women, however, were comparable within hunt types. Successful hunters spent more hours per day outside camp ($\bar{x}$ = 7.4 vs. 6.4 for unsuccessful hunters) and expended a slightly larger percentage of their hunting effort on foot ($\bar{x}$ = 87.8%) than did unsuccessful hunters ($\bar{x}$ = 84.6%). The best model predicting success of rifle deer hunters was based on hours per day spent outside camp during the hunting hours, with each additional hour increasing odds of success by 26%. For rifle elk hunters, the best model included time outside camp and a binary covariate for scouting. The odds of success increased by 418% for hunters who scouted versus those who did not, and by 18% with each additional hour per day spent hunting outside of camp. Summed model weights indicated that hours per day outside camp and scouting were most informative, and that use of an all-terrain vehicle, age, and experience were unrelated to hunter success. Both models performed reasonably well (correct classification rates of 0.74 and 0.70 for rifle deer and rifle elk models, respectively). Our study augmented the relatively limited published information about behavioral factors associated with successful harvest of deer and elk, and we recommend additional research to better unravel the nexus of success and hunter characteristics and behavior to help sustain recreational hunting and big game populations.

**KEYWORDS**

all-terrain vehicle, archery, *Cervus canadensis*, elk, hunter effort, hunter success, mule deer, *Odocoileus hemionus*, rifle hunt

The pursuit of ungulates as game animals, whether for recreation, cultural tradition, or meat, remains a popular activity on public and private lands in North America and much of the world (Cordell 2012, White et al. 2016). Strategic regulation of hunting is key for managing game population abundance, age and sex structure, and distribution (Stedman et al. 2004, Ward et al. 2008, Wam et al. 2012, Apollonio et al. 2017), with harvest rates a product of both hunter success and participation (Cooper et al. 2002). At an individual level, satisfaction often increases with hunter success (Stankey et al. 1973, Gigliotti 2000, Harper et al. 2012, Wam et al. 2012, Ebeling-Schuld and Darimont 2017) which can lead to greater hunter recruitment and retention (HRR), a common concern for many state wildlife agencies (Stedman et al. 2004, Larson et al. 2014, Mitterling et al. 2021). From 2011 to 2016, the number of big game hunters in the U.S. declined appreciably, from 11.6 to 9.2 million (U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2016). Moreover, older hunters predominate, with 24% of all hunters in the 55–64 year age class, compared to 16% of hunters being 25–34 years old (U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2016). With fewer sport hunters afield (Stedman et al. 2004, Rosenberger et al. 2021, Rosenberger et al. 2022), coupled with decreasing access for hunters on private lands (Haggerty and Travis 2006, Fontaine et al. 2019), managers have fewer options to manage game populations across landownerships, including reduced decision space to lessen depredation of crops and other resources (Walter et al. 2010, Johnson et al. 2014). Thus, investigating factors that contribute to hunter success can help inform wildlife population management and hunting season structure (Schmidt et al. 2005, Ward et al. 2008). Researchers have derived a variety of typologies to better understand hunter behavior and attitudes and thereby improve hunting season structure and HRR, such as latent-class analyses of hunter attitudes (Ward et al. 2008) and motivations (Andersen et al. 2014) and classification of hunter groups (Smith and Yuan 1991). Some typologies are linked to hunter success; for example, Boulanger et al. (2006) defined 2 typologies of muzzleloader deer (*Odocoileus* spp.) hunters, with success rates of hunters using modern muzzleloading equipment (41%) significantly greater than those using traditional equipment (34%).

Hunter success is influenced by myriad factors, such as hunter characteristics, behavior, and environmental conditions, and can be highly variable across sites and years (Rowland et al. 1997, Schmidt et al. 2005, Lebel et al. 2012, Rowland et al. 2021). General hunter characteristics of interest include age, experience, and gender, but their association with success has not been widely reported, and studies of white-tailed deer (*O. virginianus*) hunters prevail (Gigliotti 2000, Bhandari et al. 2006, Lebel et al. 2012). Older hunters were less likely to harvest an animal in some works (Bhandari et al. 2006, Boulanger et al. 2006), but age was positively related to hunter success in others (Collings 2009, Anderson 2010). Years of hunting experience was unrelated to success of deer hunters in Québec (Lebel et al. 2012) or South Dakota (Boulanger et al. 2006) and elk (*Cervus canadensis*) hunters in northern Idaho (Yuan et al. 1991). By contrast, experience was positively associated with success of elk and deer hunters in Montana (Stankey et al. 1973). Studies of gender in relation to hunter success are especially rare. Many wildlife agencies have quantified ratios of male to female hunters for a variety of hunts, but not the association between gender and hunter success. Lifetime harvest of deer by female hunters in New York was about half that of men, but data on hunt-specific success rates were not reported and differences were mostly likely due to women not hunting until later in life compared to men (Lauber and Brown 2000).

Hunter behaviors such as effort (e.g., days afield) or time preparing for a hunt (e.g., scouting) can also influence success. Hunter effort positively affected the number of white-tailed deer harvested by urban archers (Kilpatrick and Walter 1999), and Bhandari et al. (2006) found that success of antlered deer hunters was driven by hunter effort, with each additional day of hunting increasing odds of success 11%. Cooper et al. (2002) reported that harvest rates increased with hunting days for archery and rifle elk hunters. Elk hunters in Idaho who scouted had significantly higher success rates than those who did not (Yuan et al. 1991), and success of white-tailed deer hunters in Illinois was positively related to hours spent scouting (Anderson 2010). Fifty-eight percent of Michigan deer hunters surveyed ($n$ = 1,955) participated in pre-season scouting; however, benefits of scouting in relation to success were not reported (Knoche and Lupi 2010).

Transportation mode while hunting has also been associated with hunter harvest, with some modes, such as all-terrain vehicles (ATVs), presumably enabling both easier access to more remote areas where prey are located and greater travel speeds. Schmidt et al. (2005) compiled data from a variety of hunts for moose (*Alces alces*) over 5 years, during which hunters used 8 different transportation modes. They found that success rates varied widely by mode and were highest for snowmobile users (61.4%) and about half that for ATV users (30.1%). But motorized vehicles such as ATVs can also potentially hinder harvest, for example by increasing prey movement rates (Wisdom et al. 2018) or altering habitat selection (Brown et al. 2018, Spitz et al. 2019, Smith et al. 2022) during the hunt. Despite dramatic increases in recreational use and sales of off-highway vehicles in recent years across the U.S. (Cordell et al. 2005), we are unaware of published studies that relate ATV use to hunter success or vulnerability of animals to harvest.

Certain metrics related to hunter success can be managed, such as hunter density (Gratson and Whitman 2000, Hayes et al. 2002, Simard et al. 2013), hunter-prey ratios (Swenson 1982, Vales et al. 1991, Cooper et al. 2002), and road and trail density (Gratson and Whitman 2000). Variables that cannot be managed can be considered contextual (Wisdom et al. 2020) and include weather and topography. Precipitation was negatively associated with harvest of white-tailed deer in Illinois (Hansen et al. 1986) and Maine (Fobes 1945), but positively associated with harvest of Dall's sheep in Alaska (*Ovis dalli dalli*; Leorna et al. 2020). Topography did not affect success of moose hunters in Alaska (Schmidt et al. 2005), but was included in an elk hunter model developed in Montana (Smith and Yuan 1991). Success can also vary by hunting mode and weapon type (Ditchkoff et al. 1996, Boulanger et al. 2006). Archery hunters typically have lower success rates than rifle hunters, especially for branch-antlered elk, likely due to their need for proximity to prey for a killing shot (Lauber and Brown 2000, Rumble et al. 2005, Heurich et al. 2016), and deer hunters are more successful than are elk hunters (Nickerson 1990, Oregon Department of Fish and Wildlife [ODFW] 2022). Understanding factors tied to differences in success among hunter groups can aid in managing often concurrent hunting seasons across multiple wildlife units.

To better understand how hunter characteristics and behavior influence success, we obtained data about hunters during a 6-year observational study in northeastern Oregon, USA that encompassed several lines of investigation, including hunter space use (Rowland et al. 2021) and movements of non-targeted (Spitz et al. 2019, Brown et al. 2020) and targeted (Smith et al. 2022) prey during hunts. Our primary objective was to identify the most important factors in predicting harvest success from each hunter group (archery elk, rifle deer, rifle elk) across the 6 years of study by fitting competing models of success. Through modeling, we sought to describe and discriminate among a suite of hunter variables that might influence harvest, based on prior studies. We predicted that success would be greater for hunters who 1) expended more effort, such as time afield actively hunting; 2) used all-terrain vehicles (ATVs) during the hunt; and 3) had more experience hunting.

## STUDY AREA

Our study took place at the Starkey Experimental Forest and Range (Starkey), a 101-km$^2$ research site established in 1940 by the U.S. Department of Agriculture-Forest Service. Starkey was surrounded by a 2.5-m high ungulate-proof fence in 1987 that allowed for manipulative experiments at landscape scales to address a diversity of activities, such as timber harvest, hunting, and livestock grazing (Figure 1; Rowland et al. 1997, Wisdom 2005). The area available to hunters (Study Area; 7,768 ha) was characterized by a mosaic of forest and grassland vegetation types typical of the Blue Mountains ecoregion (Franklin and Dyrness 1988, Rowland et al. 1997). Mule deer (*O. hemionus*), white-tailed deer, and elk were present during the hunts; cattle grazed the study area during the summer and early fall but were usually removed before rifle deer hunts began in late September (Table 1).

Climate at Starkey is typical of that in the ecoregion, characterized by warm, dry summers and cold, moist winters (Heyerdahl et al. 2002). Annual precipitation averaged 50.4 cm, with mean temperatures of 18°C in July and −4°C in January. Mean temperatures were higher during rifle deer hunts ($\bar{x}$ = 3.2°C; range −1.7 to 21.8°C) than rifle elk hunts ($\bar{x}$ = 1.2°C; range −3.7 to 19.1°C) and were much warmer during the archery season ($\bar{x}$ = 9.1°C; range 3.1 to 30.7°C). Rainfall was minimal during the hunts, with a total of 88.4 mm during the 6 rifle deer hunts (but 38 mm in 2013), 48 mm during the rifle elk hunts (21 mm in 2012), and only 6.9 mm across all 6 archery elk hunts. See Rowland et al. (2021) for additional details about topography and dominant flora and fauna.

Hunting research at Starkey has spanned >30 years, with various tags, season lengths, start dates, and weapon types (Noyes et al. 1996, Rowland et al. 1997, Johnson et al. 2005, Davidson et al. 2012). Estimated densities of the closed but free-ranging populations of deer (primarily mule deer; white-tailed deer were rare) and elk during our study were ~1.3 deer/km$^2$ and 4.5 elk/km$^2$, which were lower than mean densities on summer range in surrounding Wildlife Management Units (WMUs) for mule deer (4.7 deer/km$^2$) but higher for elk (1.6 elk/km$^2$; Rowland et al. 2021). The Oregon Department of Fish and Wildlife (ODFW) manages for post-harvest male to female ratios of

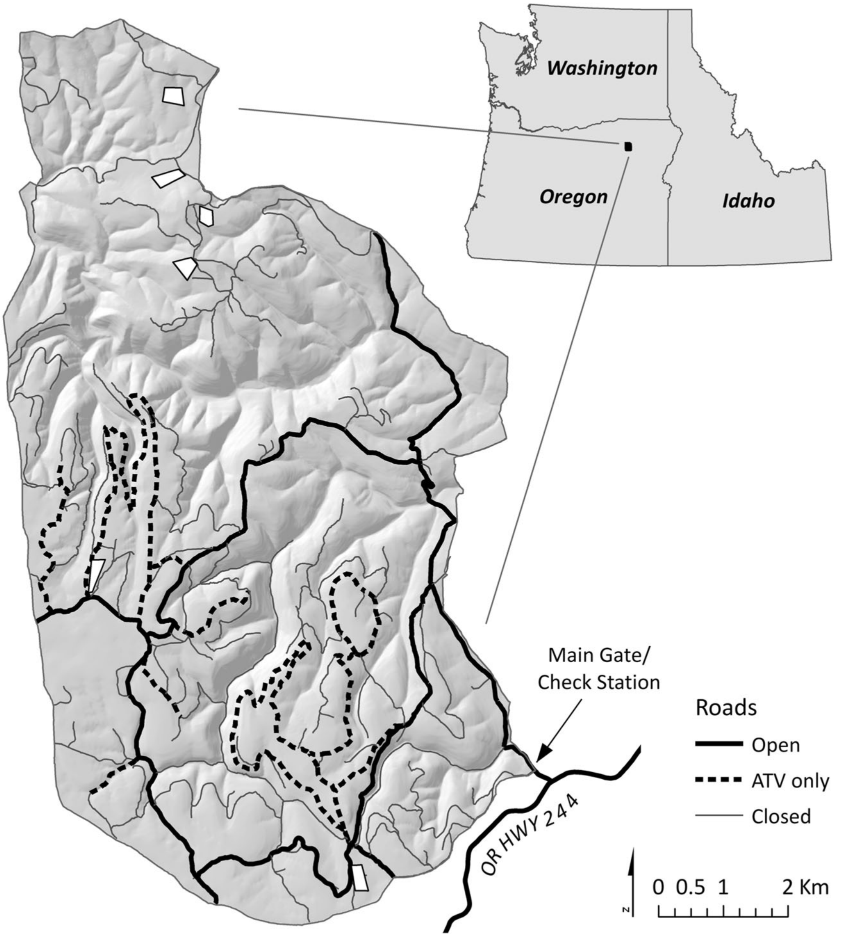


**FIGURE 1** The main enclosure of Starkey Experimental Forest and Range, northeastern Oregon, USA, and the road and all-terrain vehicle (ATV) trail system operating during controlled, 5-day hunts for antlered deer and elk, 2008–2013. All hunters entered and exited through the main gate where the hunter check station was located.

15–25:100 for deer and 10–20:100 for elk; Starkey populations are managed to maintain these ratios at a minimum.

We used a travel management system to regulate road access throughout the Starkey landscape during the hunts, in which roads designated by a sign with a green dot were open to all forms of motorized use by the public. A system of ATV trails was used to facilitate additional hunter access (Figure 1); see Rowland et al. (2021) for more details about hunt structure and road access.

## METHODS

### Hunt design and surveys

To execute the study design, ODFW implemented 3 controlled hunts annually (archery and rifle hunts for antlered elk and a rifle hunt for antlered deer), with each hunt lasting 5 days and preceded by a 5-day scouting period.

**TABLE 1** Start dates, numbers of hunters by year, hunt type, and harvest outcome (1 = successful, 0 = unsuccessful), and success rates across all years for 5-day controlled hunts for antlered deer and elk in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013.

| | Archery elk | | | Rifle deer[a] | | | Rifle elk[a] | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Date | 1 | 0 | Date | 1 | 0 | Date | 1 | 0 |
| 2008 | 30 Aug | 2 | 24 | 4 Oct | 8 | 15 | 29 Oct | 14 | 11 |
| 2009 | 29 Aug | 3 | 19 | 3 Oct | 4 | 15 | 28 Oct | 5 | 20 |
| 2010 | 28 Aug | 1 | 24 | 2 Oct | 1 | 23 | 27 Oct | 8 | 17 |
| 2011 | 27 Aug | 1 | 22 | 1 Oct | 7 | 17 | 26 Oct | 6 | 19 |
| 2012 | 25 Aug | 0 | 22 | 29 Sep | 8 | 13 | 24 Oct | 11 | 12 |
| 2013 | 24 Aug | 0 | 18 | 28 Sep | 16 | 5 | 23 Oct | 12 | 13 |
| All years | | 7 | 129 (0.051)[b] | | 44 | 88 (0.333) | | 56 | 92 (0.340) |

[a]Numbers include only those rifle deer and elk hunters with sufficient data to use in modeling hunter success. Twenty-five tags were authorized for each hunt; in addition, a small number (1–3) of tribal hunters and outfitter-guided hunters were present during some years and hunts.

[b]Values in parentheses are success rates for each hunt across the 6 years of study.

Archery hunts began the last full weekend in August and deer hunts began in late September or early October, 5 weekends after the archery season. Rifle elk hunts began the last week of October, corresponding to rifle elk hunts outside Starkey (Table 1). Twenty-five permits were allotted to hunters for each hunt through the ODFW application process, which relied on a combination of preference points and random draw. Access into Starkey was available at a single location (from State Highway 244) for hunter entry and exit (Figure 1; Rowland et al. 1997, Johnson et al. 2005). A check station was established at the beginning of each scouting period and staffed throughout the hunts to answer questions about the hunt, the road and trail system, and data collection protocols. The general public, including hunters with permits, could enter Starkey any time it was open (1 May–15 November), but hunters were required to check in during their first visit to Starkey during the controlled hunts, whether scouting or hunting.

During check-in, each hunter was provided with a paper copy of a 2-page survey prepared by ODFW to be completed during their hunt (Figure S1, available online in Supporting Information), a requirement stipulated in ODFW regulations published yearly for the Starkey hunts during our study. Hunters were encouraged to complete as much of the confidential survey as possible before their final day hunting to increase the likelihood of complete responses. Hunters were also required to complete a daily questionnaire about hours spent hunting by category (e.g., on foot vs. ATV), and how many prey animals were seen, shot at, or hit (Figure S2, available online in Supporting Information). Check station staff wrote a unique hunter ID (which could be linked to identifying information such as names) on each survey and questionnaire when they were distributed, but hunters did not write their names on the surveys. Hunters returned daily questionnaires and the completed surveys to Starkey staff or a drop box at the hunter check station before they left Starkey at the end of their hunt (Figure 1). To augment information from surveys and questionnaires, we obtained personal data from ODFW records on age and inferred gender from first names, matching these data sets with the hunter IDs.

## Hunter telemetry data

A key component of our project was using hunter location data to describe hunter space use during shooting hours when away from camp (Rowland et al. 2021). To document their movements, we provided each hunter with a small store-on-board global positioning system (GPS) unit (GPSLogger$^{TM}$, TenXsys, Eagle, ID, USA) upon arrival at Starkey and instructed hunters to wear them during hunting hours each day, including the scouting period. Rowland et al. (2021) further describe the units, their deployment, delineation of hunter camps, and censoring of telemetry data.

## Covariates

We developed a set of *a priori* covariates for potential inclusion in models to predict success of deer and elk hunters, based on our hypotheses and review of published literature about hunter success (Table 2; Yuan et al. 1991, Bhandari et al. 2006, Lebel et al. 2012, Gamo et al. 2017). Covariates initially considered included hunter characteristics or

**TABLE 2** Covariates (grouped by category) used to characterize hunters in logistic regression models to predict success during controlled rifle hunting seasons for deer and elk in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. Data were obtained from hunter questionnaires or from Oregon Department of Fish and Wildlife hunter records.[a] Example citations are provided in which the covariates are described in relation to hunter success.

| Covariate category | Covariate | Description | Example references |
|---|---|---|---|
| Age_experience | age | Hunter age | Bhandari et al. (2006); Boulanger et al. (2006) |
| | years_experience | Number of years hunting experience | Yuan et al. (1991); Lebel et al. (2012) |
| ATV[b] | n_atvs | Number of ATVs reported for the party with which the hunter was associated; values recorded as 0, 1, or >1 | |
| | used_atv | Binary variable indicating whether a hunter reported using an ATV during the hunt | Schmidt et al. (2005) |
| Behavior | hpd_out | Hours per day spent outside hunting camps during legal shooting hours (±1 hr), calculated as the total number of hours outside camp divided by number of days hunted | Yuan et al. (1991); Kilpatrick and Walter (1999); Bhandari et al. (2006) |
| | prct_on_foot | Percentage of total hunting effort that was spent on foot as reported by hunters | |
| Gender | gender | Inferred from hunter names | Lauber and Brown (2000) |
| Scouting | n_scout_days | Number of days scouting prior to hunt, based on telemetry data; values ranged from 0 to 5 but were classified as 0, 1–2, or >2 | Yuan et al. (1991); Anderson (2010) |
| | scout_yn | Binary variable denoting whether a hunter scouted at Starkey during the 5 days preceding the start date of the hunt, based on whether telemetry data were recorded during the scouting period | Yuan et al. (1991); Anderson (2010) |

[a]We considered several additional covariates for inclusion in modeling but omitted them for a variety of reasons, including collinearity with other covariates, excessive numbers of missing records, too few telemetry locations for calculation, or an insufficient sample size (e.g., $n = 6$ for weather covariates). Rejected covariates included hours per day on an ATV, preference points used to obtain a hunting permit, number of targeted prey (i.e., either deer or elk) killed in prior hunts, lunar phase and illumination, and various classes of temperature and precipitation.

[b]All-terrain vehicle.

behavior, e.g., age, gender, whether an ATV was used, or hours each day spent hunting on foot versus horseback or using an ATV (Table 2), and environmental conditions during the hunt, such as lunar phase and maximum temperatures. We included quadratic terms for some covariates, such as age, if we predicted that the effect of the covariate on hunter success might level out at some value rather than continue to increase linearly.

Except for age and gender, we used information from hunter surveys and daily questionnaires (Figures S1 and S2) to create covariates describing hunter characteristics. We derived 3 covariates that relied on hunter telemetry data: hours per day outside camp (hpd_out), number of scouting days (n_scout_days), and whether a hunter scouted (scout_yn; Table 2). For hpd_out, we used GPS data to total the time spent by each hunter outside camp during legal shooting hours (±1 hour) and divided by number of days hunted. We had previously mapped camp locations for each hunter for a prior analysis of hunter space use, using a buffer around clusters of night-time hunter locations (Rowland et al. 2021). We assumed that hunters outside camp were actively traveling to a hunting location, scouting, or pursuing game during those hours.

If 2 covariates were highly correlated based on Pearson's correlation coefficient (i.e., $|r| > 0.6$), we dropped one, retaining the one with greater management relevance, or did not use them together in the same model. Across rifle hunts, percentage time hunting on foot (prct_on_foot) was negatively correlated with percentage of time on an ATV (prct_on_atv; $r = -0.63$). There was higher variability in prct_on_foot, so we retained it for modeling. Correlation of years of experience (years_experience) and age approached our cutoff ($r = 0.59$), so we did not allow both covariates in the same model.

## Data analysis

### Modeling

We used logistic regression in a Bayesian hierarchical model of hunter success (0 = failure, 1 = success). We expected hunter success to vary by year and possibly with the lunar phase during the hunt (Rivrud et al. 2014), the weather during or just before the hunt (e.g., precipitation patterns; Fobes 1945, Lebel et al. 2012, Rivrud et al. 2014), or year-long drought conditions. However, with only 6 potentially unique lunar and weather covariate values (one for each year) for analysis of hunter success within a hunt type, we recognized that estimation and interpretation of these effects would be tenuous. Thus, rather than model weather explicitly, we treated year, our primary sampling unit, as a random effect in a generalized linear mixed model (GLMM) using Markov Chain Monte Carlo (MCMC; Hobbs and Hooten 2015) methods. We fit the following GLMM to the binary success-failure of hunter $i$ in year $j$ of the study ($y_{ij}$):

$$y_{ij} \sim Bernoulli(p_{ij})$$
$$logit(p_{ij}) = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} \ldots \beta_k x_{ki} + \delta_j,$$

where $p_{ij}$ is the expected proportion of hunters that were successful, $y_{ij}$ was the observed outcome, α was the intercept; $\beta_1$ through $\beta_k$ were $k$ coefficients for fixed effects (e.g., years of experience); and $\delta_j$ were random effects for years. We used weakly informative priors for the intercept, coefficients, and random effects. We considered ~N(0, 10), T(3, 0, 2.5; Students t-distribution), and ~Cauchy(0, 2.5) for all parameters. We compared the priors using Bayesian leave-one-out cross-validation (LOOcv; Luo and Al-Harbi 2017, Vehtari et al. 2017; also see Model selection) and other checks of MCMC convergence. We also looked at the sensitivity of the posterior distributions to the various priors (Hobbs and Hooten 2015).

### Imputation and missing values

We had missing values for 3 key covariates (years_experience, prct_on_foot, and hpd_out) in our data set, requiring imputation approaches to capitalize on all data collected, rather than omitting observations with incomplete data.

Overall, we had 13 ($n$ = 132) and 19 ($n$ = 148) incomplete records for rifle deer and rifle elk hunters, respectively, for which we imputed values. Specifically, we used multiple imputations by chained equations (mice; van Buuren 2018) and MCMC (Link et al. 2002, Brooks et al. 2011) to address the missing values in our data and predictive mean matching (PMM; van Buuren 2018) for imputation (see Appendix A for details about specific covariates used for imputing).

We centered all continuous covariates by subtracting their medians to help speed convergence and reduce collinearity between the quadratic terms and their linear counterparts. Next, we set the number of imputations $m$ = 10, close to the maximum percentage of missingness for any incomplete covariates (max = 13%; Schafer 1997). Then, we analyzed the 10 imputed data sets using logistic regression and MCMC methods. Finally, we estimated posterior distributions for parameters using 20,000 iterations in 4 chains, following a 4000-iteration burn-in. When multiple imputation is used for MCMC sampling, each imputation is run independently, making the total number of chains $m$ x 4 = 40.

We used the mice package (van Buuren and Groothuis-Oudshoorn 2011) for the R statistical environment for imputation and the brms package (Bürkner 2017) for MCMC sampling (version 4.1.1; R Core Team 2021). We used the Gelman-Rubin diagnostic (Rhat; Gelman and Rubin 1992), posterior predictive checks, trace plots, and plots of the autocorrelation function to evaluate convergence (Sinharay 2003). We assumed that sufficient convergence was obtained when all Rhat values were <1.05, posterior predictive checks looked reasonable, and there appeared to be low serial correlation in the trace plots and autocorrelation function and sufficient mixing among chains.

## Model selection

Little published literature exists relating hunter probability of success to their characteristics or behavior using empirical data (Rowland et al. 2021), so we did not produce a set of *a priori* models but rather an *a priori* list of potential covariates. We used a 4-step model selection process in which we first grouped covariates into 5 categories to predict hunter success: 1) age and experience, 2) gender, 3) ATV use, 4) scouting effort, and 5) behavior (i.e., hunting effort). We considered both linear and quadratic forms for age, years_experience, hpd_out, and prct_on_foot. Next, we identified the top model, or models, in each group using LOOcv (a lower value is better), the recommended method for comparing hierarchical models in contrast to other information-theoretic techniques (Hobbs and Hooten 2015). We brought >1 model forward if 2 or more models had similar (i.e., difference <1) LOOcv values within a covariate group. Then we constructed a list of possible combinations of the best models from each group. If there was >1 univariate model within a covariate group, we did not consider both covariates in the same model. Finally, we used LOOcv to guide model ranking among the suite of all possible combinations of the best univariate models. We evaluated the best model(s) for hunter success within each hunt type by calculating the correct classification rate (Hosmer et al. 2013) using a cut-off of 0.5 to predict hunter success (prediction > 0.5) and the area under the curve (AUC; Hosmer et al. 2013). If no quadratics were in the final set of models selected for comparisons, we calculated covariate weights, in a similar fashion to AIC weights (Burnham and Anderson 2002), for all covariates in the models considered. Covariate weights can be useful in ranking relative importance of predictors (Burnham and Anderson 2002).

# RESULTS

After removing hunters with missing data for summary statistics, 416 hunters were available for analysis, with roughly equal numbers for each of the 3 hunt types (Table 1). Harvest rates across the 6 years were nearly equal for rifle hunters (33% for rifle deer, 34% for rifle elk), which exceeded that of archery elk hunters (5%). Annual success rates were variable, ranging from 4 to 76% for rifle deer and 20 to 56% for rifle elk hunters, and from 0 to 14% for archers (Table 1).

Hunters across the 3 hunt types shared several characteristics. Distributions of hunter ages were similar across hunt types, although a larger proportion of rifle elk hunters were >50 years old and archery elk hunters were somewhat younger (Appendix B, Figures B1 and B2). Male hunters were more common than females in all hunts ($n = 370$ vs. $n = 46$, respectively), but success rates for men and women were comparable within hunt types (Appendix B, Table B1). Years of experience as reported by hunters differed considerably among hunt types, with rifle deer hunters averaging ~50% more (24.8 years; range 0 to 73 years) than that of elk hunters (rifle elk, 16.7 years, range 0 to 55 years; archery elk, 14.3 years, range 0 to 47 years).

Rifle deer hunters spent slightly less time outside camp during hunting hours ($\bar{x}$ = 6.3 hours/day) compared to both archery (6.8 hours/day) and rifle (6.8 hours/day) elk hunters. All hunters spent most of their hunting effort on foot, led by archers ($\bar{x}$ = 90.8%), followed by rifle elk (85.7%) and rifle deer (80.0%) hunters. Moreover, about half of archery and rifle elk hunters reported spending 100% of their time afield hunting on foot. Most hunters (81%), especially for elk (85%), scouted at least one day before the hunt.

Comparing hunter characteristics and behaviors by outcome revealed that successful hunters were similar in age to unsuccessful (except for archers; $\bar{x}$ = 35.7 years [range 26 to 48 years] for successful vs. $\bar{x}$ = 45.6 years [range 16 to 72 years] for unsuccessful) but spent more hours per day hunting outside camp and expended more effort on foot than did unsuccessful hunters in all hunt types (Figures B1 and B2). Years of hunting experience in relation to success, by contrast, differed across hunt types. Successful rifle elk hunters had somewhat more experience ($\bar{x}$ = 20.0 years; range 1 to 55) than did unsuccessful ($\bar{x}$ = 14.8 years; range 0 to 44), experience between rifle deer hunters was very similar ($\bar{x}$ = 24.6 years [range 0 to 73 years] for successful vs. $\bar{x}$ = 24.9 years [range 0 to 70 years] for unsuccessful), and successful archers had less experience ($\bar{x}$ = 12.3 years; range 5 to 21) than unsuccessful archers ($\bar{x}$ = 14.4 years, range 0 to 47; Figures B1 and B2). Rifle hunters who scouted were far more likely to be successful, with 38% and 41% of rifle deer and elk hunters who scouted harvesting an animal during their respective hunts, in contrast to success rates of 20% and 16%, respectively, for those who did not (Table B1). By contrast, although >80% of archers scouted, success rates were consistently low (Table B1). More rifle hunters used an ATV than did not, in contrast to archery hunters, but success rates differed little in relation to ATV use for any hunt type (Table B1).

## Models of hunter success

Given the small sample size for successful archery hunters ($n = 7$; Table 1), we only modeled success for rifle hunters. Data for modeling rifle deer and elk hunters were missing for some covariates and we imputed values for these as described in Appendix A. From the 9 covariates considered (Table 2) we developed 17 models and used 7 covariates, identified through model selection within each covariate group (Appendix C, Table C1), to create our final list of 63 competing models for each of the 2 rifle hunts. The best models from each covariate group were all univariate, with no quadratic forms. Three covariates were included in both final model sets, used_atv, gender, and scout_yn, whereas 2 were considered only in rifle deer models (age and hpd_out) and 2 only for rifle elk (prct_on_foot and years_experience; Table C1).

The best predictor of success for rifle deer hunters was the univariate model hpd_out, with probability of success reaching ~0.50 as hpd_out exceeded 10 hours (Figures 2 and 3; Table 3). The largest Rhat for parameter estimates in this model, including the intercept term, was 1.03. The second- and third-ranked models for rifle deer hunter success included hpd_out combined with scout_yn and prct_on_foot, respectively, a finding demonstrated in the univariate modeling results for these 2 covariates (Appendix D, Figure D1). The odds ratio for the best rifle deer model indicated that with each additional hour per day spent hunting outside camp, the odds of success increased by 26% (Table 3).

For rifle elk hunters, the best model included 2 covariates: hpd_out and scout_yn (Figures 2 and 3; Table 3). The largest Rhat for parameter estimates in this model, including the intercept term, was 1.02. The top-ranked model indicated that probability of success for hunters who scouted rose with increasing hours per day spent outside

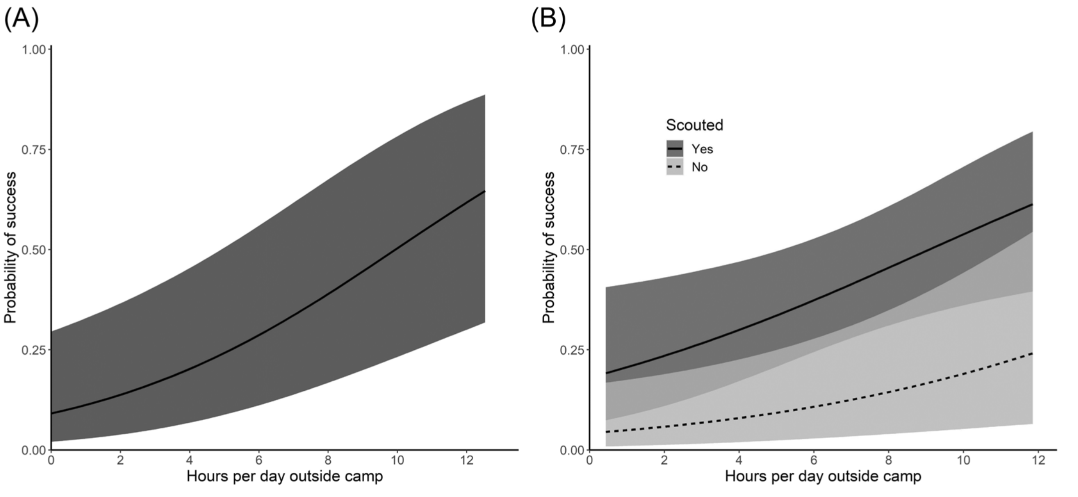


**FIGURE 2** Predictions of probability of success based on the best models for rifle deer (A) and rifle elk (B) hunters during controlled, 5-day hunts for antlered deer and elk, Starkey Experimental Forest and Range, northeastern Oregon, USA in 2008–2013. Shaded regions represent 90% credible intervals.

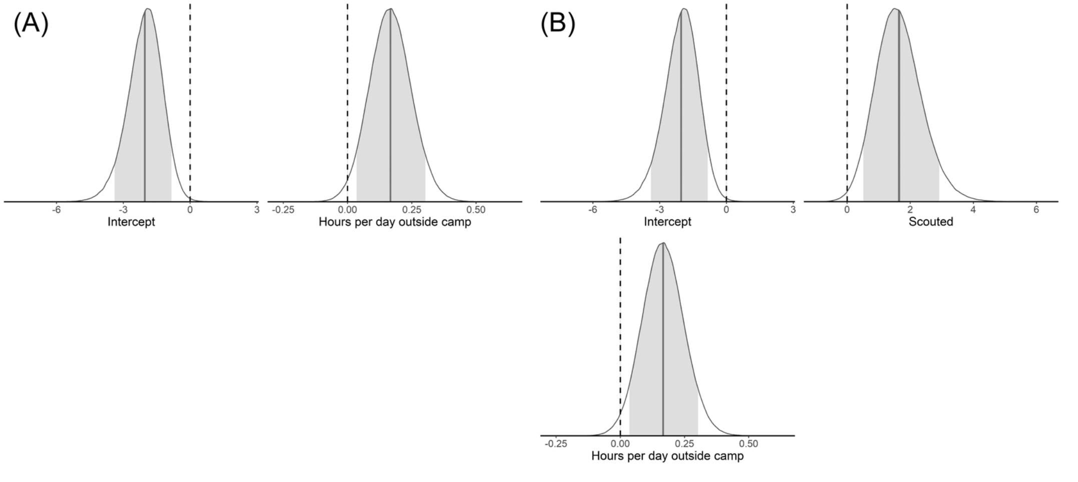


**FIGURE 3** Posterior distributions of estimates in the best logistic regression models predicting success of rifle deer (A) and rifle elk (B) hunters during controlled hunts for antlered males, Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. Shaded regions indicate 90% credible intervals of the estimated parameters, and grey vertical lines are mean values. The intercept is presented for both models, 1 covariate for the rifle deer model, and 2 covariates for rifle elk. See Table 2 for covariate descriptions.

camp, reaching about ~0.50 at 10 hpd_out. By contrast, likelihood of success for rifle elk hunters who did not scout increased minimally with hpd_out and was only 0.12 at 10 hpd_out (Figure 2). The second and third-best models for rifle elk added years_experience and prct_on_foot, respectively, to the best model. Posterior distributions from univariate models of these 2 covariates also showed relatively strong associations with success (Figure D1). Odds ratios for the best rifle elk model revealed that the odds of success increased by 418% for hunters that scouted versus those who did not, and by 18% with each additional hour per day spent outside of camp during hunting hours (Table 3).

**TABLE 3** Parameter estimates, standard errors (SE), upper and lower 90% Bayesian Credible Intervals (BCIs), and odds ratios for covariates in the best logistic regression models predicting hunter success during controlled rifle hunts for antlered deer and elk in the Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013; see Table 2 for covariate descriptions.

| Model | Parameter | Estimate | SE | Lower BCI | Upper BCI | Odds ratio (%) |
|---|---|---|---|---|---|---|
| Deer | Intercept | −0.837 | 0.720 | | | |
| | hpd_out | 0.235 | 0.085 | 0.098 | 0.378 | 26.456 |
| Elk | Intercept | −2.037 | 0.779 | | | |
| | scout_yn | 1.644 | 0.735 | 0.513 | 2.916 | 417.678 |
| | hpd_out | 0.167 | 0.081 | 0.035 | 0.303 | 18.164 |

**TABLE 4** Summed LOOcv (leave-one-out cross-validation) weights for covariates evaluated in competing models (*n* = 63 for each hunt type) developed to predict success of rifle deer and rifle elk hunters in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. See Table 2 for covariate descriptions.

| Covariate | Deer | Elk |
|---|---|---|
| Age | 0.290 | – |
| Gender | 0.202 | 0.248 |
| Hpd_out | 0.914 | 0.687 |
| Prct_on_foot | 0.409 | 0.464 |
| Scout_yn | 0.478 | 0.847 |
| Used_atv | 0.280 | 0.334 |
| Years_experience | – | 0.519 |

Summed LOOcv weights for covariates in all models considered for rifle deer were greatest for hpd_out, which ranked second among rifle elk model covariates (Table 4). Scouting was also a relatively strong predictor of success for both hunt types, but more so for rifle elk (0.847) than deer (0.478; Table 4). Both age and used_atv had relatively low summed weights for the models in which they were included, and gender was the least informative of all covariates (summed weights <0.25 for rifle deer and rifle elk models; Table 4).

The top rifle deer model performed reasonably well, with a correct classification rate of 0.74 (90% Confidence Interval [CI] for random chance = 0.49–0.62) and an AUC value of 0.830. The best model for rifle elk performed nearly as well, with a correct classification rate of 0.70 (90% CI for random chance = 0.47–0.59) and AUC = 0.737.

## DISCUSSION

Our study related hunter characteristics and behavior to success of deer and elk hunters, the latter a topic seldom addressed in published big game literature. As predicted, hunters who expended more effort, reflected by scouting and hours per day spent outside camp during hunting hours, were more successful. The best models predicting success of rifle deer and rifle elk hunters contained only these 2 covariates. Although such results may be common knowledge in the hunting community, our models quantified the increased probability of success as effort increased; for example, choosing to scout increased the odds of success for rifle elk hunters over 400%. Our findings corroborate other studies describing the benefits of scouting (Yuan et al. 1991, Anderson 2010) and effort (Cooper et al. 2002, Bhandari et al. 2006, Gamo et al. 2017) for hunter harvest.

Hunters pursuing male elk at Starkey may spend several years obtaining a permit compared to rifle deer hunters. Among hunters for whom we had preference point data, rifle elk hunters used more points ($\bar{x}$ = 9.3) than did rifle deer hunters ($\bar{x}$ = 7.3), and 74% of rifle elk hunters used ≥10 points, compared to only 18% of rifle deer hunters. Given the greater opportunity costs (years to draw) and the considerably larger reward of meat and trophy antlers, elk hunters may have been keenly motivated to spend not only more time actively hunting each day, but also more days scouting compared to deer hunters. Hunters commonly traveled to Starkey to scout before the formal hunting seasons began, but we had no data quantifying this effort because the gate was open to the public beginning 1 May and visitation during this time was not monitored by Starkey staff.

Both covariates in our best models, time spent hunting outside camp and scouting, are factors largely controlled by hunters themselves, that is, hunters can choose how much time to spend actively hunting versus time in camp and whether to arrive early for scouting. These decisions are likely closely aligned with social aspects of hunting, in that time with family and friends in hunting camp can be more (Oregon Department of Fish and Wildlife [ODFW] 2019) or equally (Ebeling-Schuld and Darimont 2017) important than a successful harvest. Decisions to scout, however, could be economically driven for some participants, if doing so requires time away from work and lost income.

Our prediction that ATV use would increase hunter success was not supported. For the entire suite of models considered for both rifle deer and rifle elk hunters ($n$ = 126), used_atv was the second least important covariate based on summed model weights, and success rates were similar for hunters who used ATVs versus those who did not (Tables 4, C1). We considered number of ATVs as a model covariate (n_atvs), assuming that hunters associated with groups using multiple ATVs might be more successful. But this covariate was far less supportive of the data than used_atv and was not brought forward in the final model set. Among the approximately 50% of Starkey hunters documented bringing an ATV, the dominant purpose selected in the daily questionnaire (S2) was to travel in and around hunting area, rather than the remaining 3 choices, i.e., scouting, game retrieval, or fuel efficiency. But even ATV users reported spending most of their time hunting on foot (74.7% for rifle deer and 81.5% for rifle elk hunters), in contrast to hunting with an ATV (18.6% and 12.1% for rifle deer and elk, respectively). Thus, despite having brought an ATV to Starkey with the intention of using it to hunt, total time spent hunting with an ATV was minimal and unlikely to have influenced success.

Our prediction that success rates would be higher for more experienced hunters was partially supported. Although this covariate did not enter either of our final models predicting hunter success, it occurred in the second-best rifle elk model and ranked third of the 6 model covariates in summed LOOcv weights (Table 4). Successful rifle elk hunters had approximately 5 years more experience than did unsuccessful, but values for this metric ranged widely. Years of experience for rifle deer hunters was essentially equal across hunt outcomes, and successful archery hunters had slightly less experience than unsuccessful. Prior published literature relating hunter success to experience reveals similarly contradictory findings, with success positively (Stankey et al. 1973) or not (Boulanger et al. 2006, Lebel et al. 2012) related to experience. Experience was somewhat correlated with age ($r$ = 0.59), and the increased age of more experienced hunters could negate benefits of experience if older hunters were less able to traverse rugged terrain or hunt long days.

Our analyses of hunter success should be considered in the larger context of other factors previously identified as influencing hunt outcome, such as density of hunters (Unsworth et al. 1993, Hayes et al. 2002), prey (Simard et al. 2013), and roads (Gratson and Whitman 2000, McCorquodale et al. 2003, Lebel et al. 2012). Hunter and prey density during the Starkey hunting study did not vary substantially among years, and road and trail density were constant. Although hunters were offered a range of open road and trail densities across Starkey during the hunts, most chose to hunt in areas with more roads, and within those landscapes selected areas close to roads when outside camp (Rowland et al. 2021). Success rates can also be influenced by timing of hunts in relation to life history events when animals can be more vulnerable to harvest, such as breeding (Hayes et al. 2002) or migration (Rivrud et al. 2016). The Starkey archery hunts were held in late August, prior to breeding and during the highest temperatures of the year, a condition likely contributing to the low success rates of this hunter group.

Weather can influence hunter success (Fobes 1945, Hansen et al. 1986, Lebel et al. 2012), and we initially explored a range of weather variables for potential inclusion in our models. Given the 5-day period for each hunt type, however, we were limited to 6 data points (1 per year) for modeling weather covariates as predictors for each hunt, which we deemed inadequate. In longer hunts more typical of deer and elk seasons, weather conditions can vary considerably, with some hunters waiting for more favorable conditions, such as snow for tracking and quieter movement afield. In such cases a larger sample size of weather covariates could have been available for modeling.

Although we lacked a sufficient sample size to model archer success, we described their characteristics because of their increasing representation in the hunting community (for example, numbers of archers increased 60% in Oregon from 1979–2019; ODFW, unpublished data), harvest rates with modern equipment such as compound bows approaching those of rifle hunters, and the utility of archers in damage hunts to alleviate impacts in urban or suburban areas (Kilpatrick and Walter 1999). Moreover, little published information exists contrasting basic characteristics of archers, such as ATV use or gender, with those of rifle hunters. Archers also contribute substantially to local economies, with equipment expenditures per hunter more than doubling ($350 to $806) from 2006 to 2016 (U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2006, 2016).

## Relation of hunter success to recruitment and retention

Wildlife populations that are hunted can be viewed as a social-ecological system, with direct and indirect feedbacks between these components (Diekert et al. 2016). Understanding cultural values impacting hunter numbers and success is therefore critical to effective wildlife management. Declining numbers of big game hunters point to the need for better recruitment and retention, especially in segments of the hunting population not currently well represented such as females and younger hunters (McFarlane et al. 2003, Shrestha et al. 2012, Gigliotti and Metcalf 2016). Moreover, hunting participation rates in the Pacific states (2%; AK, WA, OR, CA, and NV) are the lowest among all regions of the U.S. and half that of the national average (4%; U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2016). Data on success rates for female hunters are rare but, in our sample, women were as successful as men, and even more so in rifle elk hunts. Female hunters, however, constituted a small percentage of hunters at Starkey (11%) and across the U.S. (10%), and participation by women in hunting has been stable since 2006 nationwide (U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2016). Women also tend to begin hunting later in life than men, who often began hunting as teenagers (Adams and Steen 1997, Lauber and Brown 2000). If wildlife agencies can successfully recruit new female hunters through targeted outreach and education (Shrestha et al. 2012), overall harvest rates are unlikely to change, however, total hunter numbers should increase. Such increases would provide additional support for wildlife agencies to manage wildlife populations as well as bolster opportunities for a key social group to participate in outdoor recreation. Recruiting additional cohorts, such as non-Caucasian hunters, to diversify the hunting population is a goal of wildlife agencies and the outdoor recreation industry (Shrestha et al. 2012); however, we did not collect data on these metrics in our study.

As was true for gender, the age distribution of Starkey hunters resembled that of U.S. hunters nationally and was dominated by older hunters. For example, only 9% and 11% of hunters at Starkey and nationally, respectively, were <25 years old. Similarly, 30% and 38%, respectively, were >55 (U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau 2016). We found little difference in outcome (i.e., success) by hunter age. Thus, recruiting younger hunters, as presumed for recruiting more female hunters, would not be expected to increase harvest rates but instead increase the hunting population overall. But if hunter recruitment remains low in the long term, total hunter numbers will decline as older hunters leave the population. Incentive programs that pair young hunters with more experienced ones may lead to increased success for younger cohorts, in turn leading to greater satisfaction (Stankey et al. 1973, Ebeling-Schuld and Darimont 2017) and thus higher HRR rates.

## Analysis and study limitations, model performance, and inference space

Logistic regression as used in our models assumes independence between hunters, which we likely did not have. Some hunters may have been influenced by others, regardless of hunting party. We also assumed that GPS locations and times were accurate for estimating time out of camp, which we cannot verify, and some units performed poorly (Rowland et al. 2021). In addition, we assumed accurate reporting by hunters of their hunting method, daily hours spent on foot or other means, and style of hunting. These assumptions extended to ATV use, in that being a member of a group that field staff recorded at check-in as bringing one or more ATVs to Starkey did not ensure it was used for hunting, nor can we know for certain that a particular hunter used any ATV associated with the group.

Incomplete observation (hunter) records pose a problem in analysis, especially when data collection is expensive and missing data from individual hunters in an already relatively small sample size can lead to reduced precision and sometimes bias. Multiple imputation procedures, as used in our analyses, are viewed as the best alternative to dropping incomplete records, regardless of the mechanism behind the missingness. We used PMM, a non-parametric approach to imputation that has fewer assumptions than other multiple imputation approaches that are fully or partially parametric, or when other methods produce unrealistic imputations. Although PMM required a set of complete records from multiple hunters, and a model on which to base the imputations, it is not highly sensitive to misspecification of the imputation model. One downside of PMM matching is that an adequate number of donors with similar covariate values as the hunter with missing data is needed to yield reasonable imputations. A primary assumption of PMM is that the distribution of the missing record is the same as the distribution of the records from the candidate donors, which we could not verify.

Although our final models were relatively simple with few covariates, they predicted hunter success better than random chance, and had AUC values in ranges deemed by Hosmer et al. (2013) as excellent (AUC $\geq$ 0.8; rifle deer) and acceptable (0.8 > AUC > 0.7; rifle elk). What values are considered acceptable may change, however, across applications. We believe the models are robust enough to inform wildlife managers and novice hunters in eastern Oregon and elsewhere that time spent actively hunting and scouting are fundamental to success.

The controlled hunts and participating hunters we evaluated in this study resembled those in other controlled hunts in WMUs of eastern Oregon in several aspects, especially for rifle elk. For example, although Starkey hunts were limited to 5 days, days hunted by rifle deer and elk hunters ($\bar{x}$ = 3.5) were only slightly less than those reported for all rifle deer and elk hunters in controlled hunts in eastern Oregon from 2012–2015 ($\bar{x}$ = 4.6; ODFW, unpublished data). Second, success rates of rifle elk hunters in our study ($\bar{x}$ = 0.34) fell within the range of all controlled rifle elk hunts in eastern Oregon from 2012–2015 (95% CI = 0.234–0.375; ODFW, unpublished data). Success rates of Starkey rifle deer hunters during our study ($\bar{x}$ = 0.33) were below the lower 95% CI for this group in eastern Oregon WMUs (0.41; $n$ = 28 hunt units). However, inter-annual success varied widely in our study (0.04 to 0.76) likely due in part to our small sample size, and similarly varies greatly among WMUs in eastern Oregon within a year. Overall, we believe our sample of 416 deer and elk hunters was comparable to those participating in controlled hunts across this region.

Future research to build on our findings could include more investigation of the prevalence of ATV use by all 3 hunter groups, including their effect on prey movements and habitat use. Such data could be gathered as part of mandatory harvest reporting required by many state wildlife agencies. We recommend additional well-designed surveys of hunters in controlled hunts across the region to better understand not only hunter demographics, but also motivations and landscape features sought while participating in hunts. Collectively, this information could aid wildlife agencies in HRR, especially in targeting less well-represented segments such as younger, female, and Latinx hunters.

# MANAGEMENT IMPLICATIONS

Our findings quantified the specific benefits of increased effort, as measured by scouting days and hours afield, in successfully harvesting deer and elk, species that are highly valued culturally and economically in much of the western U.S. We did not document an effect of hunter age or experience on success; thus, wildlife managers should not expect harvest rates to change as hunter demographics shift over time, particularly if trends in increased hunter age continue. Wildlife managers can use our results to improve hunting season designs to better meet objectives for harvest and to educate hunters, especially those just entering the hunting community, about the explicit value of these efforts. Knowledge that helps increase the probability of harvest can ultimately translate into more satisfied hunters, given the long-realized association of success with satisfaction in prior studies, and thus potentially help recruit or retain new hunters. Our finding that harvest rates for female hunters were equal to those of males can also be used to encourage participation of this under-represented segment of the hunting population. We recommend that wildlife managers increase their understanding of the linkages between success, behavior, and hunter satisfaction through more detailed evaluation of hunt outcomes and hunter surveys centered on these topics.

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## CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

## ETHICS STATEMENT

Data collected for this study were obtained using confidential surveys, ODFW records, and GPS locations provided by hunters who were given explicit descriptions of this data collection as a requirement for participating in the controlled hunts at Starkey Experimental Forest and Range each year of the study (2008–2013). These descriptions were provided through the annual, published ODFW regulations for deer and elk hunts across the state. All data were anonymized for analysis.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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## SUPPORTING INFORMATION

Additional supporting material may be found in the online version of this article at the publisher's website.

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## APPENDIX A: IMPUTATION METHODS

Unfortunately, we had 3 model covariates of interest with missing values: years_experience, prct_on_foot, and hpd_out (Table 2). In total, we lacked 17 records for years_experience (7 rifle deer; 10 rifle elk), and 9 hunters did not report prct_on_foot (3 rifle deer; 6 rifle elk). We could not calculate hpd_out for 16 hunters because they did not carry GPS units or provided insufficient location data due to GPS issues (5 rifle deer; 11 rifle elk). Overall, we had 13 ($n = 132$) and 19 ($n = 148$) incomplete records (rows in our data) for rifle deer and rifle elk hunters, respectively, for which we imputed values.

We used age, use of an ATV (used_atv), minimum daily temperature during the hunt, and scout_yn for imputing prct_on_foot and hpd_out. We used age, gender, and used_atv to impute values for years of experience. The minimum temperature for each hunt and year was classified as high, medium, or low based on the 33rd and 66th percentiles of the minimum temperatures during the same 5-day period during the previous 30 years. Although we believed more years of data would be necessary to include weather-related covariates in our models of hunter success, we suspected the potential contribution of minimum temperature class would improve the imputation of missing values for other covariates. We did not perform covariate selection for PMM because our focus was on obtaining the best possible imputations (predictions) for our missing data, not identifying the most parsimonious model. We purposefully used covariates for imputations compatible with the analysis of the imputed data (i.e., same covariates), as suggested by Meng (1994). van Ginkel et al. (2020) provide a good reference for those concerned about the use of imputation, and more details on PMM can be found in Morris et al. (2014) and Vink et al. (2015).

Our missing covariate values could have been missing completely at random (MCAR; Scheffer 2002, van Buuren 2018, Little and Rubin 2019), missing at random (MAR), or not missing at random (NMAR). Under MCAR, missingness is just as the name implies and is not a function of any variable (response or predictor variable) in the observed data. Under MAR, the missingness is conditional on some other observed covariate in the data but not the response. For example, a hunter may fail to report years of hunting experience because of their age (i.e., forgetful). Under NMAR, the probability of missingness depends on the unobserved value of the missing data, but we cannot confirm this without the unseen data in hand or prior knowledge. The most common method for handling missing data under all 3 scenarios is listwise deletion (van Ginkel et al. 2020), which removes all records associated with a missing value before analysis. However, this approach reduces statistical power under MCAR and is biased when the data are MAR or NMAR (Baraldi and Enders 2010, van Ginkel et al. 2020).

Multiple imputation is becoming more popular for handling missing data, likely because these procedures are now easier to apply given new software such as multiple imputations by chained equations (MICE; van Buuren 2018). Multiple imputation is always better than listwise deletion because it retains all of the observed data that were expensive to collect (Scheffer 2002), is unbiased under MCAR and MAR (van Ginkel et al. 2020), and less biased than listwise deletion under NMAR, provided the missingness is less than about 25% (Schafer 1997, Scheffer 2002, van Ginkel et al. 2020). Multiple imputation involves creating *m* plausible complete versions of the incomplete data set, analyzing the *m* versions independently, and combining the results to produce final estimates with measures of precision that include the uncertainty about the missing data (van Ginkel et al. 2020).

Using predictive mean matching for imputation is less vulnerable to model misspecification than other methods, has fewer assumptions, and only uses actual observed values for imputations by borrowing observed values from a hunter with a similar predictive mean for the missing covariate (Morris et al. 2014). Thus, the method only imputes values within the range of the empirical data. Predictive mean matching requires specification of covariates without missing values for directing the imputations, and we selected those we believed to be related to the covariates with missingness.

## APPENDIX B: HUNTER CHARACTERISTICS

**TABLE B1** Number of hunters (proportion successful) by gender and whether the hunter scouted or used an all-terrain vehicle (ATV) during 5-day controlled hunts for antlered deer and elk in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. See Table 2 for descriptions of covariates.

| | Gender | | Scouted | | Used ATV | |
|---|---|---|---|---|---|---|
| Hunt type | Female | Male | Yes | No | Yes | No |
| Archery elk | 16 (0.06) | 120 (0.05) | 110 (0.05)[a] | 23 (0.04) | 65 (0.06) | 71 (0.04) |
| Rifle deer | 11 (0.27) | 121 (0.34) | 97 (0.38) | 35 (0.20) | 73 (0.34) | 59 (0.32) |
| Rifle elk | 19 (0.46) | 129 (0.39) | 129 (0.41) | 19 (0.16) | 86 (0.36) | 62 (0.40) |

[a]Three archers were missing information about whether they scouted or not prior to the hunt.

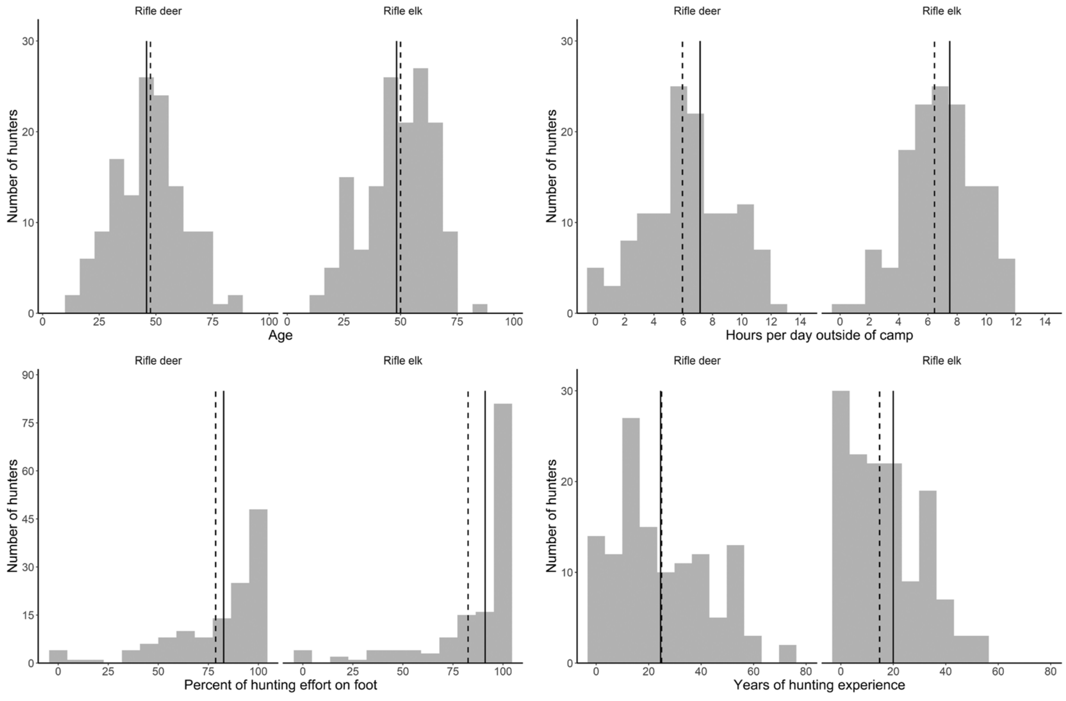


**FIGURE B1** Number of hunters for continuous covariates used to model hunter success for 5-day controlled rifle hunts for antlered deer and elk in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. Vertical lines are mean values, with solid lines representing successful hunters and dashed lines unsuccessful hunters. See Table 2 for descriptions of covariates.

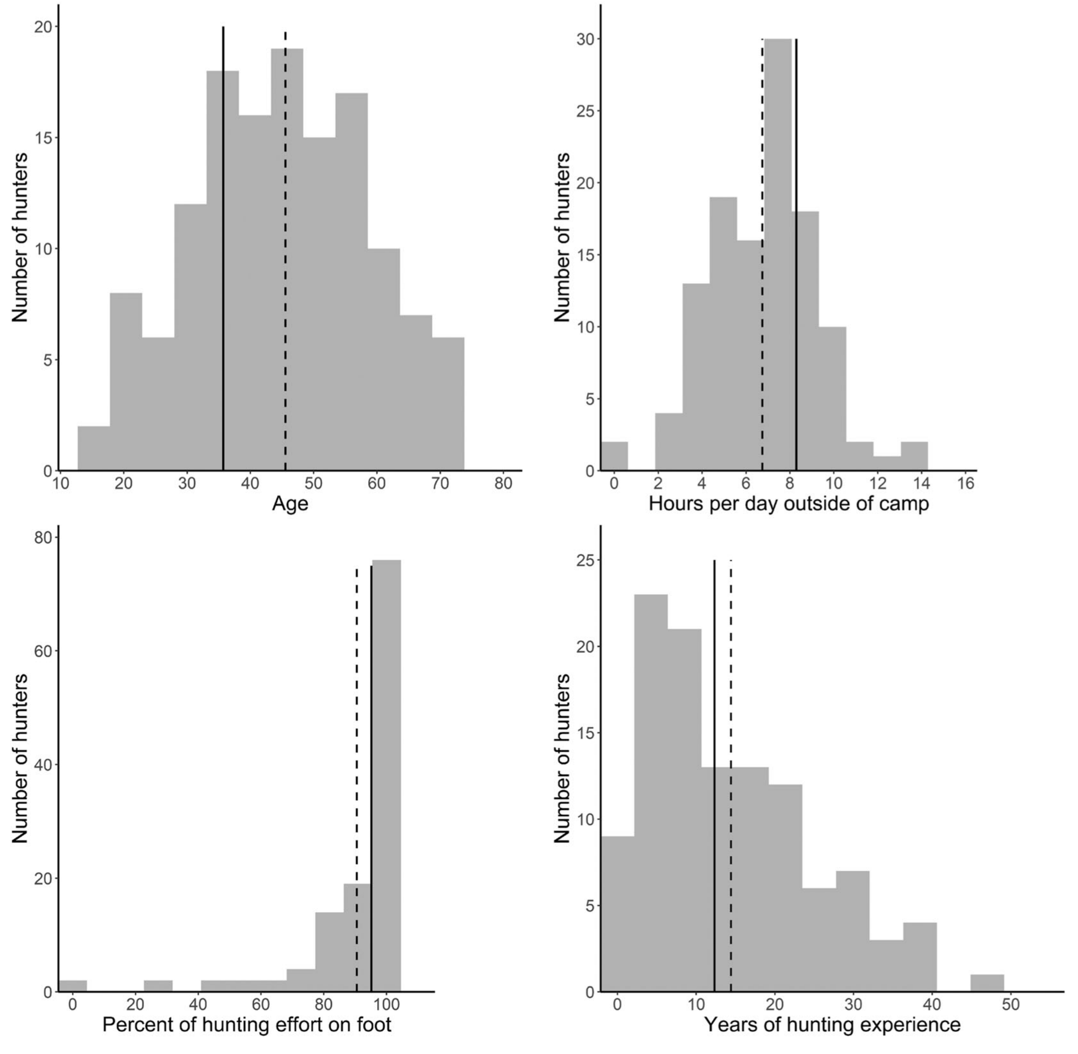


**FIGURE B2** Number of hunters by age, hours per day hunting outside camp, percent hunting on foot, and years of experience for archery hunters during 5-day controlled hunts for antlered elk in Starkey Experimental Forest and Range, northeastern Oregon, USA, 2008–2013. Vertical lines are mean values, with solid lines representing successful hunters and dashed lines unsuccessful hunters. See Table 2 for covariate descriptions.

## APPENDIX C: MODEL SELECTION RESULTS FOR COVARIATE GROUPS

**TABLE C1** Model selection results for covariates, ordered alphabetically within covariate groups, used to model success of rifle deer and elk hunters during controlled hunts for antlered males at Starkey Experimental Forest and Range, 2008–2013. The best model for each hunt type by covariate group, identified as that with the lowest leave-one-out cross-validation (LOOcv) value in the group, was brought forward to construct the final set of all possible models. See Table 2 for covariate descriptions.

| | | LOOcv | |
|---|---|---|---|
| **Covariate group** | **Model** | **Deer** | **Elk** |
| Age-experience | Age | 150.910 | 197.937 |
| | Age + $(age)^2$ | 152.629 | 198.061 |
| | Years_experience | 151.717 | 194.735 |
| | Years_experience + $(years\_experience)^2$ | 153.498 | 196.272 |
| ATV[a] | N_atvs | 153.572 | 199.929 |
| | Used_atv | 151.465 | 198.088 |
| Behavior | hpd_out | 140.871 | 195.755 |
| | hpd_out + $(hpd\_out)^2$ | 143.239 | 197.548 |
| | prct_on_foot | 149.279 | 195.065 |
| | prct_on_foot + $(prct\_on\_foot)^2$ | 151.474 | 198.790 |
| | prct_on_foot + $(prct\_on\_foot)^2$ + hpd_out | 143.823 | 199.606 |
| | prct_on_foot + $(prct\_on\_foot)^2$ + hpd_out + $(hpd\_out)^2$ | 146.552 | 202.029 |
| | prct_on_foot + hpd_out | 141.514 | 195.763 |
| | prct_on_foot + hpd_out + $(hpd\_out)^2$ | 144.033 | 198.138 |
| Gender | Gender | 152.209 | 198.325 |
| Scouting | N_scout_days | 147.823 | 193.886 |
| | Scout_yn | 145.630 | 191.773 |

[a]All-terrain vehicle.

## APPENDIX D: UNIVARIATE MODEL RESULTS

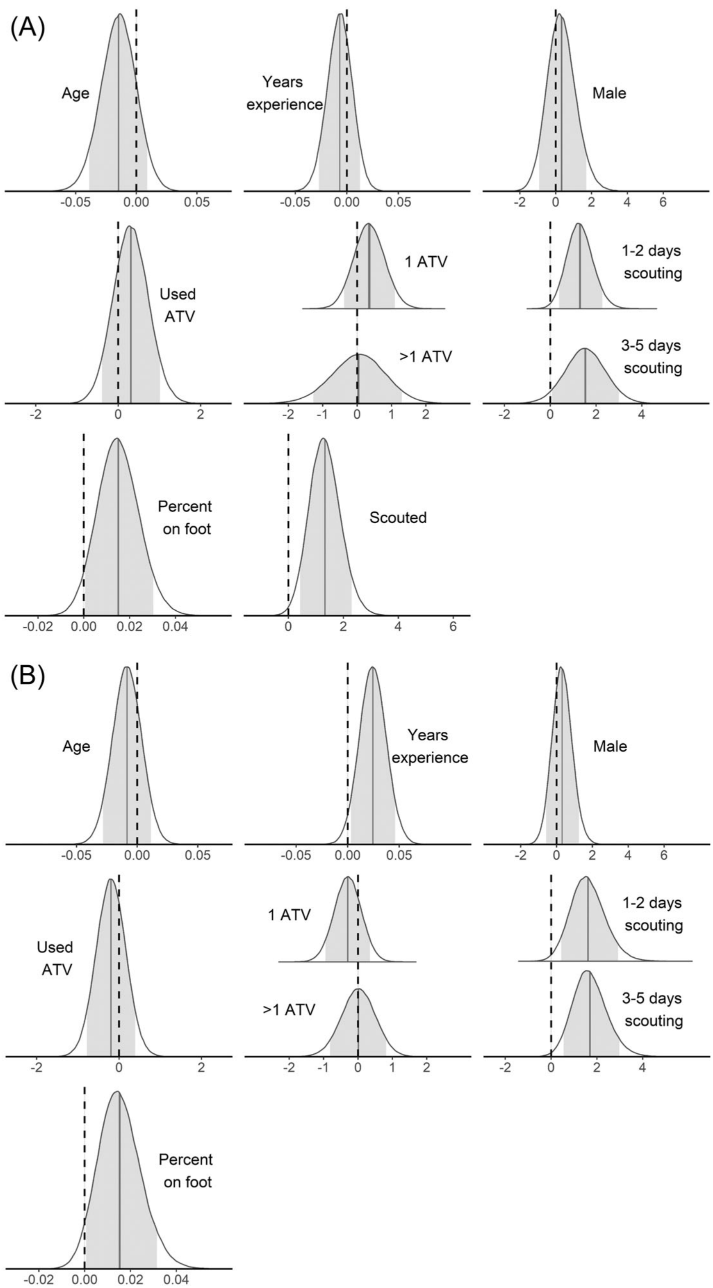


**FIGURE D1** Posterior distributions of univariate models for each covariate in the final model set (*n* = 63) for logistic regression models predicting success of rifle deer (A) and rifle elk (B) hunters during controlled hunts for antlered males at Starkey Experimental Forest and Range, 2008–2013. (Covariates in the final models are not displayed; see Figure 3). Shaded regions indicate 90% credible intervals of the estimated parameters, and grey vertical lines are mean values. See Table 2 for covariate descriptions.