Original Article

Determinants of mortality type in a high altitude Andean context using a multivariable logit regression model in Puno, Peru

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ABSTRACT

Understanding the determinants of mortality type is central to evidence-based public health, particularly in high-altitude Andean regions where demographic, clinical, and health-system factors intersect. This study aimed to identify factors associated with the type of death (natural versus violent) in the Puno region, Peru, in 2024, using a parsimonious and statistically robust logit modeling framework. A cross-sectional analytical design was applied to the entire population of registered deaths (n = 6,455), of which 3,701 cases with complete cause-of-death information were retained for multivariable analysis. Logistic regression models were estimated by maximum likelihood, with backward elimination based on likelihood-ratio tests to ensure parsimony and inferential stability. The final multivariable model included nine predictors, including clinical causes of death, demographic characteristics, health insurance coverage, place of registration, and necropsy status. The model performance was high, with a Nagelkerke R^2 of 0.658 and a classification accuracy of 98.7%, indicating excellent probabilistic discrimination. Odds-ratio estimates showed that primary and tertiary causes of death, male sex, increasing age, health insurance type, province, and registration in health facilities significantly increased the probability of natural death. In contrast, secondary causes and necropsy were inversely associated. A reduced model that included only the first three causes of death preserved strong predictive capacity (Nagelkerke R^2 = 0.272; accuracy = 97.9%), highlighting the dominant explanatory role of multi-cause mortality coding. These findings suggest that high-quality civil registration data, combined with rigorously specified logit models, can accurately characterize mortality patterns in high-altitude regions. This study provides actionable epidemiological evidence to support mortality surveillance, health-system planning, and risk stratification in the Peruvian Andes and comparable low-resource, high-altitude contexts.

Keywords: High-altitude population, Logistic regression, Mortality causes, Public health surveillance

Introduction

Mortality patterns constitute a core indicator of population health and an essential input for evidence-based public health planning. Globally, non-communicable diseases—particularly ischemic heart disease, stroke, chronic respiratory diseases, cancer, and diabetes—account for the majority of deaths, while infectious causes remain highly relevant in low- and middle-income settings and among vulnerable populations. Recent Global Health Estimates confirm that demographic aging, epidemiological transition, and unequal exposure to modifiable risk factors continue to reshape the distribution of causes of death worldwide, with marked regional heterogeneity [1-6]. In Peru, mortality reflects this dual burden. National reports indicate that diseases of the circulatory system, neoplasms, infectious and parasitic diseases, and respiratory conditions dominate mortality statistics, with substantial disparities between urban and rural areas and across geographic regions. The COVID-19 pandemic

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further amplified these inequalities, disproportionately affecting older adults and populations with limited access to timely health care, while reinforcing the role of comorbidities and socioeconomic vulnerability in mortality risk [7-12].

High-altitude regions introduce additional complexity into mortality dynamics. Living under chronic hypobaric hypoxia, as in the Andean region of Puno, has been associated with distinctive physiological adaptations and disease profiles, particularly for respiratory, cardiovascular, and infectious conditions [13-18]. Evidence suggests that altitude may modulate susceptibility, severity, and outcomes of respiratory diseases, including pneumonia and COVID-19, through environmental, biological, and health-system pathways. However, empirical, population-level analyses explicitly addressing causes and types of death in high-altitude Andean settings remain scarce [19-24].

From a methodological perspective, logistic regression models have become a standard tool for analyzing binary outcomes, such as natural versus violent death. Logistic models allow simultaneous assessment of multiple demographic, clinical, and contextual predictors, yielding interpretable measures of association through odds ratios while controlling for confounding effects. Their widespread application in epidemiology—from hospital mortality prediction to cause-specific death analyses—demonstrates their robustness for risk stratification and public health decision-making [25-29].

Despite advances in global and national mortality research, there is limited evidence integrating detailed cause-of-death information with sociodemographic and contextual variables to explain the type of death in high-altitude regions of Peru. Addressing this gap is critical to tailoring prevention strategies, improving the quality of death certification, and guiding resource allocation across geographically and socially diverse settings. Therefore, this study aims to identify and quantify factors associated with death type (natural versus violent) in the Region of Puno in 2024, using a multivariable logit model applied to population-level mortality records. By doing so, it contributes context-specific evidence to the broader literature on mortality determinants in high-altitude Andean populations.

Materials and Methods

This study adopted a quantitative, explanatory, and observational design with a cross-sectional analytical approach to identify factors associated with the type of death (natural versus violent) in the Region of Puno, Peru, in 2024. The design is appropriate for population-level mortality analyses in which exposure and outcome variables are observed simultaneously, and no intervention is applied, allowing estimation of associations rather than causal effects.

The study population comprised all registered deaths in the Region of Puno in 2024, totaling 6,455 records, obtained from official mortality registration systems aligned with the International Statistical Classification of Diseases and Related Health Problems (ICD-11). Because the analysis used the complete universe of registered deaths, no sampling procedure was applied, thereby avoiding sampling bias and maximizing representativeness at the regional level. Records included demographic, geographic, administrative, and medical information recorded at the time of death certification by authorized health personnel.

For multivariable modeling, only records with complete information on causes of death were eligible. Consequently, 3,701 records were included in the logistic regression analyses, while 2,754 records were excluded due to missing or incomplete cause-of-death data. This exclusion criterion was applied to ensure the model's internal validity and the accurate interpretation of cause-related predictors.

The dependent variable was the type of death, coded as a binary outcome: natural death (reference category) and violent death (including homicide, suicide, traffic accidents, occupational accidents, and other external causes). This dichotomization is consistent with epidemiological and forensic classifications commonly used in mortality research.

The independent variables included 13 predictors derived from death certificates and administrative records: (1) first cause of death, (2) second cause of death, and (3) third cause of death, coded according to ICD-11 categories; (4) type of health insurance; (5) sex; (6) age in years; (7) province of death; (8) place of death registration (health facility, domicile, or other); (9) performance of necropsy (yes/no); (10) ethnicity; (11) marital status; (12) educational level; and (13) month of death. Categorical variables were incorporated into the models using dummy (indicator) variables, with one category designated as the reference group in each case, following standard regression practices.

Age was treated as a continuous variable in years, allowing estimation of the incremental change in odds associated with aging. Causes of death were entered as grouped ICD categories to preserve clinical relevance while maintaining statistical stability. The primary analytical strategy was binary logistic regression, selected because the outcome variable is dichotomous and the objective was to estimate the probability of natural versus violent death as a function of multiple predictors. Logistic regression is widely used in epidemiology for mortality modeling due to its ability to handle mixed variable types, control for confounding, and produce interpretable odds ratios (ORs).

Logistic regression is a statistical modeling method used to analyze and determine the relationship between a categorical dependent variable (specifically binary, with two possible outcomes, such as yes/no, success/failure, or positive/negative) and one or more independent variables, also called predictors. These predictors may be quantitative (continuous or discrete) or qualitative (categorical). Unlike linear regression, which estimates a constant outcome, logistic regression estimates the probability that a given event occurs. The model is based on the logit (sigmoid) function, which transforms a linear combination of predictors into a value bounded between 0 and 1, allowing direct probabilistic interpretation of the outcome.

Model estimation was performed using the maximum likelihood method, which identifies parameter values that maximize the likelihood of observing the data given the model. Regression coefficients (β) were exponentiated to obtain odds ratios; OR $>$ 1 indicated increased odds of natural death and OR $<$ 1 indicated reduced odds, or, conversely, increased odds of violent death, depending on coding.

Model selection and evaluation

To obtain a parsimonious and statistically robust model, a backward stepwise selection procedure based on the likelihood ratio (LR) test was applied. The procedure began with a full model including all candidate predictors, followed by sequential removal of variables that did not contribute significantly to model fit, as assessed by the LR test at each step. This approach is recommended for logistic regression when the objective is explanatory modeling rather than pure prediction.

Model performance and goodness-of-fit were evaluated using several complementary criteria. The Nagelkerke pseudo-R^2 was used to assess the proportion of variance explained by the model, with values above 0.40 interpreted as an excellent fit in probabilistic terms. Classification performance was evaluated using overall accuracy, defined as the proportion of correctly classified cases, with thresholds proposed in multivariate analysis literature to characterize model quality. The statistical significance of individual predictors was evaluated using the Wald test with a two-sided significance level of $\alpha = 0.05$.

The study was conducted using secondary, anonymized administrative data, with no direct interaction with human subjects and no access to personally identifiable information. All procedures complied with national regulations on the use of public health data for research purposes and adhered to ethical principles for epidemiological studies based on routinely collected data. Because the analysis involved aggregated and de-identified records, informed consent was not required.

Results and Discussion

The results of this study reveal a clear and consistent set of factors associated with the type of death in the Region of Puno during 2024, highlighting the combined influence of medical, demographic, and contextual variables in a high-altitude Andean setting. From the total of 6,455 registered deaths, 3,701 records with complete cause-of-death information were included in the multivariable analysis. Descriptive findings showed that mortality in the region was dominated by natural causes, particularly acute respiratory infections, respiratory failure, septicemia, and cardiovascular conditions, with a marked predominance among males and individuals aged 50 years and older. These patterns are consistent with national and global mortality profiles but exhibit distinct regional features linked to altitude, population structure, and access to health services.

Death course in Puno

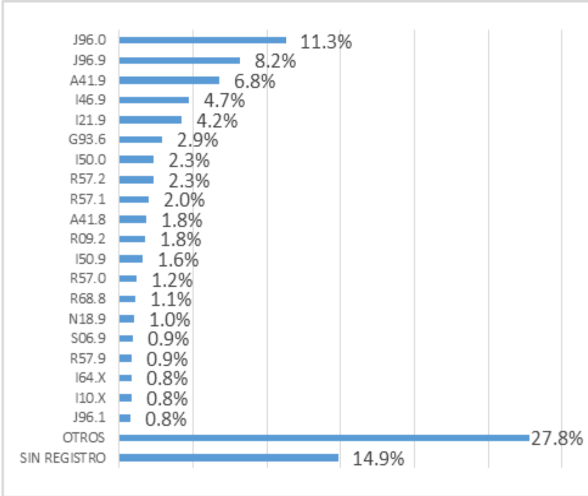

Figure 1. Leading cause of deaths in the Puno region, Peru – 2024.

Figure 1 summarizes the distribution of deaths according to the first recorded cause of death in the region of Puno during 2024. Among the 6,455 registered deaths, acute and chronic conditions of the respiratory and cardiovascular systems predominated. Acute respiratory infections (ICD-11: J96.0) constituted the leading cause, accounting for 11.3% of all deaths, followed by unspecified respiratory failure (J96.9) with 8.2%. Septicemia of unspecified origin (A41.9) represented 6.8%, highlighting the continued relevance of severe infectious processes as direct causes of mortality. Cardiovascular causes also showed a substantial contribution, particularly unspecified cardiac arrest (I46.9; 4.7%) and acute myocardial infarction without further specification (I21.9; 4.2%).

Neurological and circulatory complications such as cerebral edema (G93.6; 2.9%), congestive heart failure (I50.0; 2.3%), unspecified heart failure (I50.9; 2.3%), cardiogenic shock (R57.0; 1.6%), and unspecified cerebrovascular accident (I64.X; 0.8%) further reinforced the dominance of non-communicable diseases in the mortality profile. Conditions related to shock—septic (R57.2; 2.3%), hypovolemic (R57.1; 2.0%), and unspecified shock (R57.9; 0.9%)—were also notable, reflecting the severity and late presentation of critical illnesses. Chronic kidney disease (N18.9; 1.0%), chronic respiratory failure (J96.1; 0.8%), essential hypertension (I10.X; 0.8%), and intracranial trauma (S06.9; 0.9%) were observed at lower but relevant frequencies.

Collectively, a wide range of other diagnoses accounted for 27.8% of deaths, indicating substantial heterogeneity in less frequent causes, while 14.9% of records lacked specification of the first cause of death. Overall, the figure illustrates a mortality structure strongly dominated by respiratory infections, septic processes, and cardiovascular conditions, consistent with international classifications of leading causes of death and the epidemiological transition described by the World Health Organization [30].

Gender

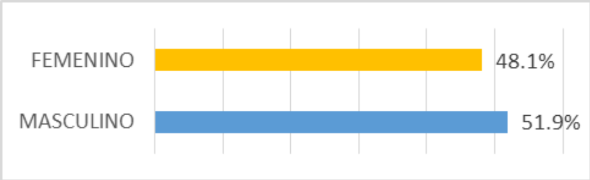

Figura 2. Gender of deaths in the Puno region, Peru – 2024.

Also, **Figure 2** describes the distribution of deaths in the Region of Puno in 2024 by type of health insurance and sex. Of the 6,455 registered deaths, a clear predominance was observed among individuals affiliated with the Seguro Integral de Salud (SIS), which accounted for 78.62% of all cases. This finding reflects the strong dependence of the regional population on the public health insurance system, particularly among socially and economically vulnerable groups. In contrast, affiliation with other insurance schemes was minimal; notably, only 0.05% of deceased individuals were covered by the Sanidad de la Fuerza Aérea del Perú (FAP), underscoring the marginal contribution of military or highly specialized insurance systems to the overall mortality structure in the region.

Regarding sex distribution, mortality was slightly higher among men, who represented 51.9% of all deaths, compared with 48.1% among women. Although the difference is modest, this pattern is consistent with widely documented sex differentials in mortality, where men often exhibit higher mortality risks associated with occupational exposure, behavioral factors, and a greater prevalence of certain chronic and acute conditions. Together, these results highlight the combined influence of health-system coverage and demographic characteristics on mortality patterns in the Region of Puno in 2024, providing important context for interpreting subsequent multivariable analyses.

To estimate the logistic regression model, 3,701 records were used from the total of 6,455 registered deaths, as the remaining 2,754 records lacked information on the cause of death and were therefore excluded from the multivariable analysis. The final model was obtained after the fifth step of a backward stepwise selection procedure based on the likelihood ratio, through which only predictors with a statistically significant contribution to the model were retained.

After the fifth processing step, the model achieved a Nagelkerke R^2 of 0.657630, exceeding the 0.40 threshold and indicating an excellent probabilistic fit according to McFadden's [17] criteria. In addition, the classification table showed an overall accuracy of 0.98703053, which is considered excellent according to the guidelines of Hair *et al*. [10], reflecting a very high proportion of correctly classified cases. The estimated logistic regression model is expressed as:

$$P(Y) = 1/(1 + e^{\wedge}(-(0{,}693 + 0{,}179\,X1 - 0{,}663\,X2 + 0{,}176\,X3 + 0{,}551\,X4 + 1{,}135\,X5 + 0{,}035\,X6 + 0{,}099\,X7 + 1{,}456\,X8 - 1{,}532\,X9))\,) \quad (1)$$

Interpretation of the odds ratios (ORs) indicates that the first cause of death increases the odds of natural death by 19.7% (OR = 1.197), while the second cause of death reduces the odds of natural death (OR = 0.515), thus increasing the likelihood of violent death. The third cause of death increases the odds of natural death by 19.3% (OR = 1.193). Likewise, type of health insurance (OR = 1.736), sex (OR = 3.111), age in years (OR = 1.036 per additional year), province of death (OR = 1.104), and place of death registration (OR = 4.290) all increase the probability of natural death. In contrast, the performance of a necropsy substantially reduces the odds of natural death (OR = 0.216), indicating a higher probability of violent death when a necropsy is conducted. Overall, the first and third causes of death, type of insurance, sex, age, province, and place of registration are positively associated with natural death. In contrast, the second cause of death and necropsy are inversely associated, favoring violent death classification **(Table 1)**.

Four predictor variables were excluded during the backward selection process because they did not contribute significantly to the model. In the first step, *marital status* was removed due to a Wald statistic close to zero (0.086) and a non-significant P-value (0.769). In the second step, *ethnicity* was excluded (Wald = 0.236; P = 0.627). In the third step, the *month of death* was removed (Wald = 0.051; P = 0.358). In the fourth step, *educational level* was eliminated (Wald = 1.878; P = 0.171). After the fifth step, only the predictors with a statistically significant effect in the logistic model remained, yielding a parsimonious and statistically robust specification.

Table 1. Interpretation of the odds ratios (ORs).

Variables	B	S. Error	Wald	Sig.	OR
X1: First cause of death	0.179446	0.035	26.359	0	1.196555
X2: Second cause of death	−0.663168	0.158	17.587	0	0.515217
X3: Third cause of death	0.176109	0.032	30.696	0	1.192569
X4: Type of health insurance	0.55137	0.162	11.529	0.001	1.73563
X5: Sex	1.134842	0.399	8.081	0.004	3.110683
X6: Age (years)	0.035155	0.007	25.75	0	1.03578
X7: Province of death	0.09867	0.055	3.25	0.071	1.103666
X8: Place of death registration	1.4563	0.229	40.348	0	4.290125

X9: Necropsy	−1.5315	0.413	13.748	0	0.216202
Constant	0.69323	3.314	0.044	0.834	2.000155

Note: B = logistic regression coefficient; OR = odds ratio; Sig. = significance level (P-value). The dependent variable corresponds to the type of death (natural vs. violent).

The multivariable logistic regression model demonstrated excellent explanatory and classification performance, with a Nagelkerke pseudo-R^2 of 0.66 and an overall accuracy exceeding 98%, indicating intense discrimination between natural and violent deaths. The analysis showed that the first and third causes of death significantly increased the probability of natural death. In contrast, the second cause of death was inversely associated with this outcome, suggesting that combinations of underlying and contributing causes provide additional information beyond a single primary diagnosis. Demographic factors also played a relevant role: male sex and increasing age were associated with higher odds of natural death, reflecting the cumulative burden of chronic and degenerative conditions in older populations.

A logistic regression model was estimated using three predictive variables—first, second, and third causes of death—and a binary dependent variable (type of death: natural vs. violent). The analysis included 3,701 records with complete information on causes of death. The final model was obtained in the first step of the backward stepwise selection procedure based on the likelihood ratio, as all three predictors were statistically significant **(Table 2)**.

Table 2. A logistic regression model was estimated using three predictive variables.

Variables	B	SE	Wald	Sig.	OR
X1: First cause of death	0.17699	0.022	65.587	0	1.193619
X2: Second cause of death	−0.276071	0.061	20.324	0	0.758759
X3: Third cause of death	0.192968	0.018	109.67	0	1.212844
Constant	3.842189	1.232	9.723	0	46.627427

After estimation using the likelihood-ratio backward method, the model achieved a Nagelkerke R^2 of 0.271823, indicating a good probabilistic fit, as it falls within the range of 0.20–0.40 proposed by McFadden [17]. The classification table showed an overall accuracy of 0.97865442, considered excellent by Hair *et al*. [10], indicating that the model correctly classified nearly 98% of cases. The estimated logistic regression equation is:

$$Y = \frac{1}{1 + e^{-(3{,}842\, +\, 0{,}177\, X1\, -\, 0{,}276\, X2\, +\, 0{,}193\, X3)}} \tag{2}$$

The odds ratio analysis indicates that the first cause of death significantly increases the odds of natural death by 19.4% (OR = 1.194). Similarly, the third cause of death increases the odds of natural death by 21.3% (OR = 1.213), suggesting that contributing or underlying medical conditions reinforce the classification of deaths as natural. In contrast, the second cause of death shows an inverse association (OR = 0.759), reducing the odds of natural death and therefore increasing the likelihood of violent death classification. Overall, these findings demonstrate that even when only cause-of-death variables are considered, the logistic model exhibits strong discrimination, underscoring the relevance of multiple-cause mortality analysis for understanding death patterns in the Puno region.

Contextual and health-system–related variables further contributed to explaining mortality patterns. The type of health insurance and the place of death registration, particularly deaths recorded in health facilities, were strongly associated with natural death, underscoring the role of institutional care and formal certification processes. In contrast, the performance of a necropsy was associated with lower odds of natural death, indicating its greater use in cases of suspected or confirmed violent death. Geographic variation by province showed a modest but positive association with natural death, reflecting territorial differences in health infrastructure and population characteristics across the region.

Overall, these findings contribute robust empirical evidence on mortality determinants in a high-altitude Andean context and demonstrate the value of logistic regression models that integrate multiple causes of death with sociodemographic and administrative variables. The results underscore the importance of considering not only primary causes but also contributing conditions and contextual factors when analyzing mortality, providing actionable insights for public health planning, mortality surveillance, and improving death certification practices in regions such as Puno.

Conclusion

This study provides robust empirical evidence on the determinants of death type (natural versus violent) in the Region of Puno, Peru, in 2024, using population-level mortality data and multivariable logistic regression. The findings confirm that mortality in this high-altitude Andean context is predominantly driven by natural causes, particularly respiratory, infectious, and cardiovascular conditions. At the same time, violent deaths represent a smaller but clearly differentiated subset. The high explanatory power and classification accuracy of the estimated models demonstrate the suitability of logistic regression for analyzing mortality patterns in settings characterized by demographic, geographic, and health-system heterogeneity.

The full model shows that multiple dimensions jointly shape the probability of natural death. Medical factors, captured through the first and third causes of death, substantially increase the likelihood of natural death, whereas the second cause of death and the performance of a necropsy are inversely associated, reflecting their stronger linkage to violent or externally caused deaths. Demographic and contextual variables—such as sex, age, province of death, type of health insurance, and place of death registration—also play a significant role, highlighting the importance of considering both biological and institutional determinants in mortality analyses. These results underscore the value of integrating multiple-cause-of-death information with sociodemographic and administrative data to improve the interpretability of mortality statistics.

The reduced model based solely on the first, second, and third causes of death further demonstrates that cause-of-death information alone has strong discriminatory capacity, achieving excellent classification accuracy despite lower explanatory power than the full model. This finding supports the relevance of multiple-cause mortality approaches in contexts where sociodemographic variables may be incomplete or inconsistently recorded. From a public health perspective, the results emphasize the need to strengthen prevention and early management of respiratory and infectious diseases in high-altitude regions, improve the completeness and quality of death certification, and refine forensic and necropsy practices to ensure accurate classification of violent deaths. Overall, this study contributes context-specific evidence for mortality surveillance and health policy planning in the Peruvian Andes and offers a methodological framework applicable to other regions with similar epidemiological and geographic characteristics.

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