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Causal Effects of Social Vulnerability and Multimorbidity on Tooth Loss in Chile: A National Survey Analysis

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Abstract

Tooth loss reflects cumulative biological and social processes across the life course. However, population-level causal evidence on the influence of structural social vulnerability and multimorbidity on tooth-loss severity remains limited in middle-income contexts. This study evaluated the causal impacts of social vulnerability and multimorbidity on tooth-loss severity and retention in Chilean adults. We analyzed nationally representative data from the Chilean National Health Survey 2016–2017 (N = 5,165 adults aged ≥20 years). Outcomes comprised ordinal severity (y_1: functioning dentition, moderate loss, severe loss, edentulism) and continuous tooth count (y_2). Exposures included a Social Vulnerability Index (SVI, 0–1) and Multimorbidity Score (MS, 0–1). We estimated confounder-adjusted proportional-odds and survey-weighted linear regression models. Population-averaged causal contrasts were obtained via g-computation comparing 75th and 25th exposure percentiles, with 95% confidence intervals from probability-proportional-to-size bootstrap (1,000 replications). Age-dependent edentulism trajectories were generated using discrete-time Markov projections. In the weighted population, 72.6% retained functional dentition whereas 5.5% were edentulous. Increasing SVI from 0.091 to 0.345 was associated with a 0.093-point severity increase and 1.52 fewer teeth. Increasing MS from 0.00 to 0.20 was associated with a 0.059-point severity increase and 1.23 fewer teeth. SVI showed larger population-averaged effects than multimorbidity. Structural social vulnerability and multimorbidity independently influence tooth-loss severity, with socioeconomic disadvantage showing stronger distributional effects across the life course.

Keywords: tooth loss; oral health; causality; socioeconomic factors; chronic disease

1. Introduction

Tooth loss is among the most prevalent oral health conditions worldwide, reflecting the combined effects of dental caries, periodontal disease, and broader social determinants [1,2]. Despite substantial advances in preventive and restorative care, the population-level burden of severe tooth loss and edentulism has remained persistently high over recent decades. International assessments consistently identify tooth loss as a major contributor to disability and functional limitation, with disproportionately higher prevalence among older adults, women, rural populations, and socioeconomically disadvantaged groups [1–3]. This enduring burden the limited capacity of clinical advances alone to

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address social and structural drivers, underscoring persistent inequalities in oral health outcomes [3–6]. Although some high-income countries have reported gradual declines, marked global and regional disparities persist [1]. Consequently, tooth loss is widely recognized as both a marker of cumulative oral pathology across life curse [7–15] and as a determinant of reduced quality of life and elevated systemic health risks [15–17].

These global trends are mirrored in Chile, where rapid population ageing and persistent inequalities in access to oral health services shape the national distribution of tooth loss. Data from the Chilean National Health Survey 2016–17 (ENS 2016–17) [18,19] indicates that 91.7% (95% CI: 88.6–94.0) of adults aged 35–44 years have functional dentition. This proportion decreases sharply to 30.2% among adults aged 65–74 years (95% CI: 24.9–36.0). Moderate and severe tooth loss affect 25.4% and 6.9% of adults, respectively, whereas edentulism reaches 4.8%. Furthermore, Chile exhibits high levels of multimorbidity: 54.9% of adults—and 82.4% of older adults—live with two or more chronic diseases. Results from the ENS 2016–17 demonstrate steep gradients in tooth retention by age, educational attainment, and multimorbidity burden, indicating that tooth loss in Chile is embedded within broader patterns of social vulnerability, chronic disease clustering, and unequal access to preventive and restorative care [12,18,19]. Despite ongoing local health-system reforms [20–22], pronounced oral-health disparities persist across sociodemographic groups [16].

Understanding the causal determinants of tooth loss in this context is essential for informing prevention strategies. However, establishing causality from observational data presents substantial methodological challenges. Although numerous studies have reported associations between tooth loss and systemic conditions [3,5,9,10], most rely on observational designs vulnerable to confounding, selection bias, and reverse causation. Beyond these methodological limitations, the clinical complexity of tooth loss as an outcome poses additional challenges. Risk patterns vary substantially with age, socioeconomic position, and chronic disease burden [16], and the clinical course spans multiple stages—from functional dentition to edentulism—each with distinct health implications. Simplifying this continuum into binary outcomes may obscure clinically relevant variation and complicate causal interpretation.

Despite these methodological and clinical challenges, recent advances in oral epidemiology—including longitudinal designs [12], fixed-effects estimation [14], as well as the application of directed acyclic graphs (DAGs) [13] have enhanced conceptual clarity regarding probable causal pathways linking tooth loss to systemic health. However, rigorous evidence of population-level causation remains limited, particularly in middle-income countries characterized by pronounced social gradients, elevated multimorbidity, and inequitable healthcare access. Addressing this evidence gap requires clear causal frameworks that explicitly define estimands, specify identifying assumptions, and systematically control for confounding in observational data.

Applying these frameworks to social vulnerability [16] and multimorbidity [12] in observational data presents specific methodological challenges. First, these exposures are not randomly distributed but strongly correlated with age, health behaviors [23], healthcare access, and health status [24], creating complex confounding structures. Second, tooth loss may simultaneously represent an outcome of prior exposures and a marker of accumulated disadvantage [16], raising concerns about reverse causation. Addressing these challenges requires explicit causal estimands, careful confounder identification, and analytic strategies that approximate counterfactual contrasts.

This study aimed to estimate the causal effects of social vulnerability and multimorbidity on tooth loss in the Chilean adult population, examining how these determinants shape both cumulative tooth-loss burden and clinical severity across the life course. By translating causal effect estimates into age-conditional risk profiles, we provide evidence to inform oral health policy and integrated prevention strategies targeting socially and clinically vulnerable populations.

 doi:10.20944/preprints202603.1535.v1

2. Materials and Methods

2.1. Data Source and Study Population

We analyzed data from the Chilean National Health Survey 2016–2017 (ENS 2016–17) [25], a nationally representative survey conducted by the Ministry of Health using a stratified, multistage, cluster sampling design. In total, 6,233 individuals completed the baseline survey, of whom 5,520 received home visits from trained nurses and 5,306 completed oral examinations. For the present study, the analytical sample was restricted to adults aged ≥20 years who had completed the oral examination. Individuals younger than 20 years and those without oral examination data were excluded, resulting in a final analytical sample of 5,165 adults. All analyses incorporated the survey weights corresponding to each ENS module to account for the complex sampling design and to ensure national representativeness.

2.2. Variables and Measurements

2.2.1. Tooth–Loss Outcomes

Remaining natural teeth were counted during home-based oral examinations conducted by trained and calibrated nurses (inter-rater reliability $\kappa = 0.85$) [25]. Tooth loss was operationalised using two outcomes. Severity (y_1) was classified as an ordinal variable with four categories: functional dentition (≥20 teeth), moderate loss (10–19 teeth), severe loss (1–9 teeth), and edentulism (0 teeth). Tooth count (y_2) was analysed as a continuous variable (range 0–28 teeth).

2.2.2. Explanatory Variables

Variables were organized into three domains: sociodemographic factors, health behaviors, and systemic chronic conditions. Sociodemographic variables included age, sex, region, area of residence (urban/rural), years of schooling, employment status, indigenous ethnicity, and household sanitation index. These were collected via baseline questionnaires. Health behaviors included current tobacco use and alcohol consumption in the past 12 months, assessed during nurse visits. Chronic conditions were identified from self-reported physician diagnoses and laboratory results following ENS standard definitions and diagnostic criteria. Conditions included diabetes mellitus, hypertension, obesity, joint diseases, cardiovascular events, respiratory diseases, chronic renal failure, thyroid disease, depression, cancer, liver disease, reduced mobility, and coagulation disorders. Table 1 presents variable definitions and survey weights.

 doi:10.20944/preprints202603.1535.v1

Table 1. Conceptual domains, study variables, and operational definitions used in the causal analysis of tooth loss. ENS, Chile, 2016-17.

Conceptual Domain	Variable	Operational Definition	Type	n sample	N Weighted	Survey Weights
1. Sociodemographic context	Age	Age in completed years at the time of the survey.	Continuous	5,165	11,692,408	Fexp_F1p_Corr
	Sex	Self-reported biological sex (male/female).	Categorical	5,165	11,692,408	Fexp_F1p_Corr
	Region	Administrative region of usual residence.	Categorical	5,165	11,692,408	Fexp_F1p_Corr
	Area of residence	Urban or rural classification.	Categorical	5,165	11,692,408	Fexp_F1p_Corr
	Years of schooling	Completed years of formal education.	Continuous	5,118	11,615,702	Fexp_F1p_Corr
	Employment status	Current employment status (employed, unemployed, inactive).	Categorical	5,093	11,537,266	Fexp_F1p_Corr
	Indigenous ethnicity	Self-identification as belonging to an indigenous group (yes/no).	Categorical	5,165	11,692,408	Fexp_F1p_Corr
	Sanitation index	Household sanitation conditions (acceptable/deficient).	Categorical	5,021	11,476,668	Fexp_F1p_Corr
2. Health-related behaviors and lifestyles	Tobacco use (binary)	Current tobacco use (yes/no).	Binary	5,165	11,476,668	Fexp_F1p_Corr
	Alcohol consumption (binary)	Alcohol use during the last 12 months (yes/no).	Binary	5,023	12,678,675	Fexp_F2p_Corr
3. Systemic chronic conditions	Diabetes mellitus	Self-reported medical diagnosis and blood glucose greater $\geq$ 126 (yes/no).	Binary	5,165	13,083,296	Fexp_EX1p_Corr
	Arterial hypertension	Self-reported treatment for blood pressure and average of three blood pressure readings: systolic $\geq$ 140 and diastolic $\geq$ 90 (yes/no).	Binary	5,157	13,080,025	Fexp_F1F2p_Corr
	Obesity	BMI $\geq$ 30 kg/m^2 (yes/no).	Binary	5,128	13,027,276	Fexp_F2p_Corr
	Osteoarthritis	Self-reported diagnosis (yes/no).	Binary	5,131	12,994,346	Fexp_F2p_Corr
	Rheumatoid arthritis	Self-reported diagnosis (yes/no).	Binary	5,141	13,022,802	Fexp_F2p_Corr
	Chronic renal failure	Self-reported diagnosis (yes/no).	Binary	5,154	13,080,905	Fexp_F2p_Corr
	Thyroid disease	Self-reported diagnosis (yes/no).	Binary	5,142	13,056,503	Fexp_F2p_Corr
	Depression	Self-reported medical diagnosis and use of antidepressant medication in the last two weeks (yes/no).	Binary	5,101	11,574,117	Fexp_F1p_Corr
	Acute myocardial infarction	Self-reported diagnosis (yes/no).	Binary	5,141	11,655,091	Fexp_F1p_Corr
	Stroke	Self-reported diagnosis (yes/no).	Binary	5,133	11,649,241	Fexp_F1p_Corr
	Cancer	Self-reported diagnosis (yes/no).	Binary	3,397	6,527,715	Fexp_F2p_Corr
	Liver disease	Self-reported diagnosis (yes/no).	Binary	5,144	13,062,027	Fexp_F2p_Corr
	Asthma	Self-reported diagnosis (yes/no).	Binary	5,144	13,048,519	Fexp_F2p_Corr
	COPD	Self-reported diagnosis (yes/no).	Binary	5,155	13,080,897	Fexp_F2p_Corr
	Reduced mobility	Self-reported reduced mobility (yes/no).	Binary	5,165	11,692,408	Fexp_F1p_Corr
	Coagulation disorders	Self-reported diagnosis (yes/no).	Binary	5,165	13,096,377	Fexp_F2p_Corr
4. Clinical tooth-loss severity (y_1)	Tooth-loss status	Ordinal categorical variable: functional dentition ($\geq$ 20 teeth), moderate (10–19), severe (1–9), edentulism (0).	Ordinal	5,165	13,096,377	Fexp_F2p_Corr
5. Cumulative tooth-loss burden (y_2)	Remaining teeth	Total number of remaining natural teeth (0–28).	Continuous	5,165	13,096,377	Fexp_F2p_Corr

Notes:(*) To consider the complex survey design, we utilized the survey weights according to the user manual instructions. The survey weights indicated in this table were used for the descriptive and inferential analysis.

 doi:10.20944/preprints202603.1535.v1

2.2.3. Socioeconomic Vulnerability Index (SVI)

We constructed a Socioeconomic Vulnerability Index (SVI) based on five indicators representing structural dimensions of social disadvantage. Four components were binary and coded as 1 = vulnerable and 0 = not vulnerable: employment status (unemployed or economically inactive vs employed), indigenous ethnicity (self-identified membership of an indigenous group), household sanitation (deficient vs acceptable, according to Chilean Ministry of Social Development and Family criteria [26]), and area of residence (rural vs urban). Educational attainment was incorporated as a continuous component based on completed years of formal schooling. To ensure comparability with the binary indicators, years of schooling were rescaled to a 0–1 range using min–max normalization and subsequently inverted so that higher values corresponded to greater socioeconomic vulnerability (i.e., fewer years of education). Formally, let V_{ik} denote the k-th vulnerability component for individual i. Binary components take values in 0,1, and the education component takes values in [0,1] after normalization and inversion. The SVI for individual i was defined as the unweighted mean of the five components:

$$\mathrm{SVI}_i = \frac{1}{5}\sum_{k=1}^{5} V_{ik} \tag{1}$$

By construction, $SVI_i \in [0,1]$, with higher values indicating greater socioeconomic vulnerability. The index was calculated at the individual level without incorporating survey weights in its construction. Survey weights were applied only when describing component prevalences to account for the complex sampling design. Table 2 summarizes the SVI components, source variables, and sample characteristics.

Table 2. Components and construction of the Socioeconomic Vulnerability Index (SVI).

SVI Component	Operational Definition	Type	N (sample)	Survey Weights
Employment vulnerability	Current employment status: unemployed or economically inactive (vs employed).	Binary	5,093	Fexp_F1p_Corr
Indigenous vulnerability	Self-identification as belonging to an indigenous group (yes/no).	Binary	5,165	Fexp_F1p_Corr
Sanitation vulnerability	Household sanitation conditions: acceptable or deficient.	Binary	5,021	Fexp_F1p_Corr
Educational attainment (normalized)	Completed years of formal education, normalized to a 0–1 scale.	Continuous (0–1)	5,118	Fexp_F1p_Corr
Rural vulnerability	Urban or rural classification of area of residence.	Binary	5,165	Fexp_F1p_Corr

Notes: 1) The analytical sample comprised 5,165 adults aged ≥20 years with completed oral examination. 2) N (sample) reflects the number of participants with non-missing data for each specific component within the analytical sample; variation in N is due to item-level missingness. 3) All components were obtained from the sociodemographic module (F1); weighted estimates were derived using Fexp_F1p_Corr to account for the complex sampling design. 4) The composite SVI was calculated as the unweighted mean of the five components (scaled 0–1). A complete-case approach was applied at the index level. A total of 4,910 participants (95.1% of the analytical sample) had complete data for all five components and were included in the final SVI computation.

2.2.4. Morbidity Score (MS)

We constructed a Multimorbidity Score (MS) to quantify cumulative chronic disease burden at the individual level. Fifteen chronic conditions were included: diabetes mellitus, arterial hypertension, obesity, osteoarthritis, rheumatoid arthritis, chronic renal failure, thyroid disease, depression, acute myocardial infarction, stroke, liver disease, asthma, chronic obstructive pulmonary disease (COPD), reduced mobility, and coagulation disorders. Cancer was initially excluded from the index due to substantial missingness (62.2% of data valid). Each condition was coded as a binary indicator, with a value of 1 if the condition was present and 0 if absent, based on self-reported physician diagnosis and/or laboratory criteria (for diabetes). Missing values were coded as NA. Let K=15 denote the total

 doi:10.20944/preprints202603.1535.v1

number of included conditions. The number of observed (non-missing) conditions for individual i was defined as:

$$O_i = \sum_{k=1}^{K} I(C_{ik} \neq \text{NA}) \tag{2}$$

where $I(\cdot)$ is the indicator function.

The count of conditions present was computed as:

$$S_i = \sum_{k=1}^{K} C_{ik} \tag{3}$$

where S_i ranges from 0 to 15.

A normalised version (MS_norm) of the index was then calculated as:

$$MS_i = \frac{S_i}{K}, \qquad 0 \leq MS_i \leq 1 \tag{4}$$

Thus, MS_i ranges from 0 (no chronic conditions) to 1 (all 15 conditions present).

MS was computed as an unweighted individual-level index. Survey expansion factors were applied when describing condition prevalences but were not incorporated into the index calculation itself. A complete-case approach yielded 4,890 participants (94.7% of the analytical sample) with valid data across all 15 conditions. Table 3 summarizes MS components and sample characteristics.

Table 3. Chronic conditions included in the Multimorbidity Score (MS).

MS Component	Operational Definition	Type	N (sample)
Diabetes mellitus	Self-reported medical diagnosis and fasting blood glucose $\geq$ 126 (yes/no).	Binary/Categorical	5,165
Arterial hypertension	Self-reported treatment for blood pressure and average of three blood pressure readings: systolic $\geq$ 140 and diastolic $\geq$ 90 (yes/no).	Binary/Categorical	5,157
Obesity	Body mass index $\geq$ 30 kg/m^2 (yes/no).	Binary/Categorical	5,128
Joint diseases (osteoarthritis)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,131
Joint diseases (rheumatoid arthritis)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,141
Cardiovascular events (acute myocardial infarction)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,141
Cardiovascular events (stroke)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,133
Respiratory diseases (asthma)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,144
Respiratory diseases (COPD)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,155
Chronic renal failure	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,154
Thyroid disease	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,142
Depression	Self-reported medical diagnosis and use of antidepressant medication in the last two weeks (yes/no).	Binary/Categorical	5,101
Liver disease	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,144
Reduced mobility	Self-reported reduced mobility (yes/no).	Binary/Categorical	5,165
Coagulation disorders	Self-reported medical diagnosis (yes/no).	Binary/Categorical	5,165
Cancer (*)	Self-reported medical diagnosis (yes/no).	Binary/Categorical	3,397

Notes: (*) Cancer was excluded *a priori* from the primary MS construction due to substantial missingness (62.2% valid observations). A sensitivity analysis including cancer as an additional component was conducted to assess robustness.

2.2.5. Component Contribution and Interaction Analyses

To evaluate the structural robustness of the composite indices and the relative contribution of key components, we conducted additional analyses at both the index and model levels. First, we performed leave-one-out sensitivity analyses for each index. For the SVI, alternative versions were constructed by sequentially excluding each component, with particular attention to educational attainment given its continuous nature and structural relevance. For the MS, analogous recalculations were performed excluding diabetes mellitus and, separately, including cancer despite its higher missingness. For each alternative specification, we examined both distributional stability and changes in causal effect

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estimates for tooth-loss outcomes relative to the primary index definitions. Second, to assess the marginal contribution of dominant components, we estimated models in which education (for SVI) and diabetes (for MS) were included explicitly alongside the composite index. This allowed evaluation of whether the observed associations reflected cumulative burden or were primarily driven by a single influential component. Third, effect modification was assessed by introducing interaction terms between SVI and MS in the primary outcome models. Interaction was evaluated on the appropriate model scale and interpreted within the prespecified causal framework. These analyses ensured that the primary exposure definitions used in the causal models were structurally stable and not disproportionately influenced by specific components.

2.3. Causal Framework

Using the primary specifications of SVI and MS (both continuous and scaled 0–1), we estimated causal effects on tooth-loss outcomes within the potential outcomes framework [27,28]under three core assumptions: temporal precedence, conditional exchangeability (no unmeasured confounding), and correct model specification. Temporal precedence is supported by both biological and social ordering. Tooth loss is cumulative and irreversible, whereas key SVI components—educational attainment, employment status, and place of residence—are typically established early in adulthood and remain stable. Similarly, MS reflects the progressive accumulation of chronic conditions over time. Although the ENS 2016–17 data are cross-sectional, the structural and clinical determinants captured by SVI and MS precede cumulative tooth loss, supporting causal interpretation under a life-course perspective. Conditional exchangeability was addressed by adjusting for age, sex, tobacco use, and alcohol consumption—well-established determinants of both social and clinical exposures and oral health outcomes. These confounders were specified as a apriori based on epidemiological theory. While residual confounding from unmeasured factors (e.g., access to dental care or oral hygiene practices) cannot be excluded, the ENS provides extensive covariate information. Sensitivity analyses further evaluated robustness to alternative model specifications. Under these assumptions, regression coefficients were interpreted as conditional causal effects, and population-averaged contrasts were estimated via parametric g-computation [29], yielding average treatment effects consistent with structural interpretations of intervention effects [30,31].

2.3.1. Multi-Variable Regression Approach

Given that SVI and MS were modeled as continuous exposures (scaled 0–1), we employed regression-based adjustment to estimate conditional exposure–outcome associations while preserving the continuous structure of both indices. This approach allows direct estimation of adjusted effects under the prespecified causal assumptions. For the ordinal severity outcome (y_1), defined as increasing levels of tooth-loss severity, we fitted proportional odds logistic regression models:

$$\text{logit}\Big[\Pr\Big(Y^1 > j \mid SVI, MS, X\Big)\Big] = \alpha_j + \beta_{\text{svi}}\, SVI + \beta_{\text{ms}}\, MS + \gamma^\top X \tag{5}$$

where $j \in \{0, 1, 2\}$ indexes cumulative severity thresholds, X denotes the confounder vector (age, sex, tobacco use, alcohol consumption), and β_{svi} and β_{ms} represent adjusted log-odds ratios associated with a one-unit increase in SVI or MS, assuming proportional odds across thresholds.

For the continuous outcome (y_2: number of remaining teeth), we estimated linear regression models:

$$E\Big[Y^2 \mid SVI, MS, X\Big] = \alpha + \beta_{\text{svi}}\, SVI + \beta_{\text{ms}}\, MS + \gamma^\top X \tag{6}$$

where β_{svi} and β_{ms} represent the expected change in the number of remaining teeth per unit increase in SVI or MS, conditional on covariates.

 doi:10.20944/preprints202603.1535.v1

2.3.2. Causal Interpretation

Under the assumptions of temporal precedence, no unmeasured confounding, correct model specification, and positivity, the regression coefficients β_{svi} and β_{ms} can be interpreted as conditional causal effects. These assumptions were considered plausible based on: (i) comprehensive confounder measurement within ENS 2016–17; (ii) the biological and social plausibility that cumulative vulnerability and chronic disease burden precede tooth loss; and (iii) adequate overlap in exposure distributions across confounder strata.

2.3.3. Average Treatment Effects (ATE) via G-Computation

To complement conditional regression estimates and obtain population-averaged causal contrasts, we estimated Average Treatment Effects (ATEs) using g-computation (standardization). For each exposure (SVI and MS), we defined the ATE as the difference in expected outcomes under two hypothetical exposure levels corresponding to the 75th and 25th percentiles of the observed distribution. Formally, letting a_{75} and a_{25} denote the 75th and 25th percentile values of the exposure, the estimand was defined as:

$$\text{ATE} = E[Y(a_{75})] - E[Y(a_{25})] \tag{7}$$

The estimator was obtained by standardization over the empirical covariate distribution:

$$\widehat{\text{ATE}} = \frac{1}{n}\sum_{i=1}^{n}\left(\widehat{E}(Y \mid A = a_{75}, X_i) - \widehat{E}(Y \mid A = a_{25}, X_i)\right) \tag{8}$$

where $\widehat{E}(Y \mid A, X)$ denotes predicted values from the fitted regression models and X_i represents the observed covariate vector for individual i. This procedure yields marginal (population-averaged) causal contrasts while preserving the continuous nature of the exposures. Confidence intervals for the ATE were estimated using non-parametric bootstrap resampling with 1,000 replications, thereby accounting for uncertainty in both model estimation and outcome prediction.

2.3.4. Statistical Software and Pipeline

Data management and survey-weighted descriptive analyses were conducted using Stata version 18.0 (Stata Corp, College Station, TX, USA). Causal regression models and g-computation for ATE estimation were implemented in Python (version 3.x) using statsmodels for proportional odds and ordinary least squares regression, and numpy/pandas for standardization and bootstrap procedures.

Figure 1 summarizes the causal analysis workflow. Using the ENS 2016–2017 survey, we defined an analytical sample comprising adults aged $\geq$ 20 years who completed the oral examination and had complete information on exposures, outcomes, confounders, and the dental expansion factor. Three variable domains were specified *a priori* on epidemiological and causal grounds. The outcome domain included y_1, an ordinal indicator of tooth-loss severity, and y_2, the continuous number of remaining teeth. The exposure domain comprised the Social Vulnerability Index (SVI) and the normalised Multimorbidity Score (MS), both modeled as continuous variables scaled from 0 to 1. The confounder set included age, sex, tobacco use, and alcohol consumption, selected to satisfy causal assumptions.

Multi-variable regression models were fitted to estimate conditional exposure–outcome associations: a proportional-odds logistic regression model for y_1 and a survey-weighted linear regression model for y_2, incorporating the dental expansion factor (`Fexp_F2p_Corr`). Regression coefficients (β_{svi}, β_{ms}) were interpreted under the assumptions of conditional exchangeability, positivity, and correct model specification.

Population-level causal contrasts were obtained using g-computation. For each exposure, average treatment effects (ATEs) were estimated by contrasting predicted outcomes under hypothetical shifts from the 25th to the 75th percentile of the exposure distribution and averaging over the observed covariate distribution with application of survey weights. Ninety-five per cent confidence intervals were derived using probability-proportional-to-size (PPS) non-parametric bootstrap resampling (1,000 replications), ensuring consistency with the survey expansion factor.

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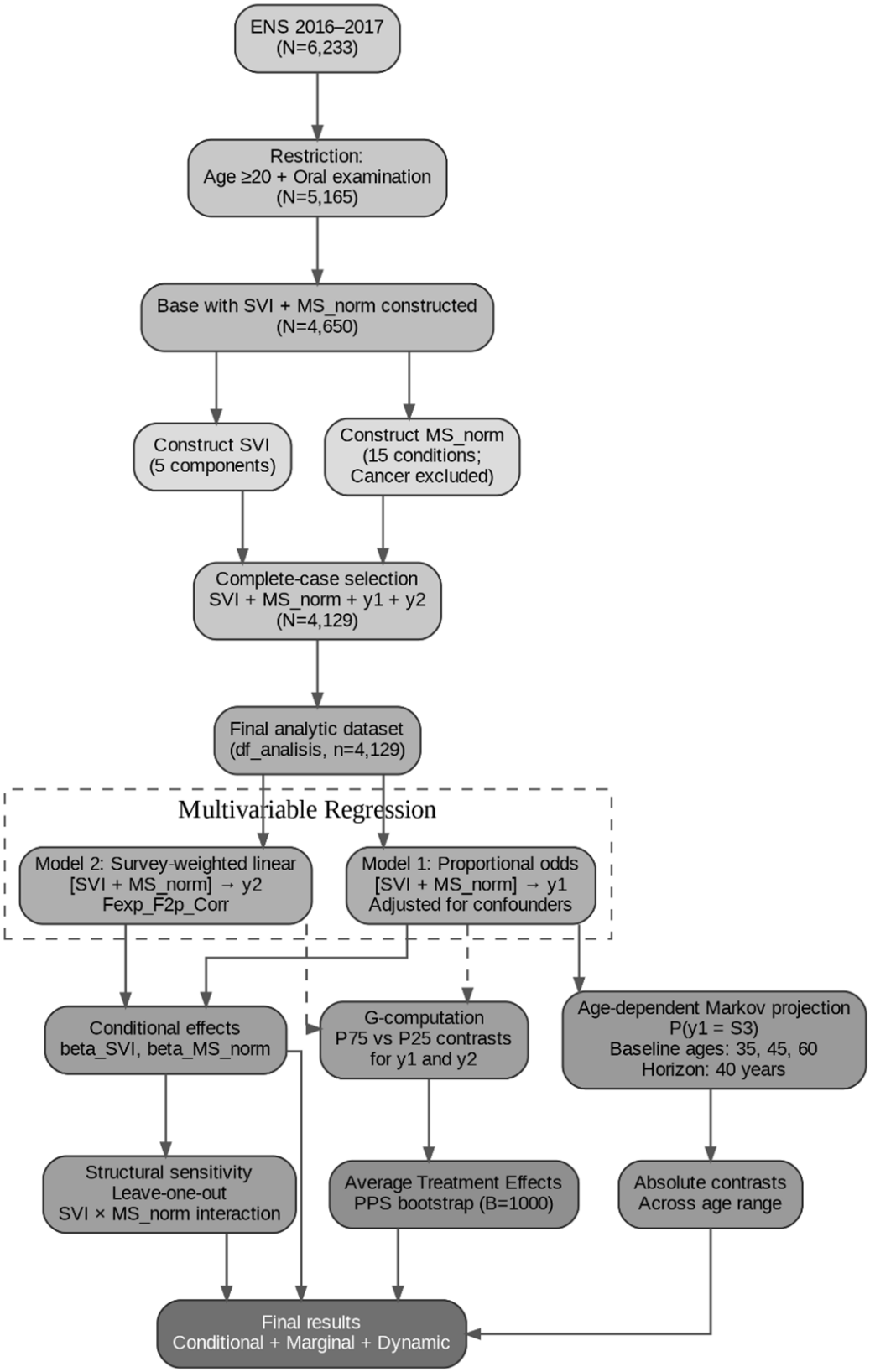

Figure 1. Causal analysis pipeline for tooth-loss determinants. The workflow progresses from the ENS 2016–2017 dataset ($N = 6{,}233$) to the restricted analytic sample ($N = 5{,}165$; adults $\geq$ 20 years with oral examination). Composite exposures (SVI and MS_norm) were constructed and analyzed using proportional-odds regression for y_1 (ordinal severity) and survey-weighted linear regression for y_2 (remaining teeth), adjusted for age, sex, tobacco use, and alcohol consumption. Conditional effects were obtained from model coefficients, and population-averaged effects were estimated via g-computation (P25 vs P25) with bootstrap confidence intervals. Age-dependent counterfactual projections of $P(y_1 = S3)$ and structural sensitivity analyses completed the analytical framework.

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2.3.5. Age-Dependent Markov Projection

To translate regression-based estimates into clinically interpretable age-dependent projections, we implemented a discrete-time, non-homogeneous Markov extension of the fitted proportional-odds model for y_1. Let

$$p_k(a, X) = \Pr(y_1 = k \mid a, X), \qquad k \in \{0, 1, 2, 3\} \tag{9}$$

denote the age-specific predicted probability of each tooth-loss severity state from the ordinal model, where a is age and X represents the determinant profile (SVI, MS_{norm}, and covariates) held constant under each counterfactual scenario. These probabilities were used to parameterize time-dependent transition matrices between severity states (S0–S3), with edentulism (S3) specified as an absorbing state.

Let π(a) denote the row vector of state probabilities for y_1 at age a. The evolution of the severity distribution was defined as:

$$\pi(a + 1) = \pi(a)P(a) \tag{10}$$

where $P(a)$ is the age-specific transition matrix calibrated to the model-predicted probabilities. Trajectories were simulated over a 40-year horizon under sustained exposure scenarios corresponding to the 25th and 75th percentiles of SVI and MS_{norm}. The initial state distribution at each baseline age (35, 45, and 60 years) was defined by the model-predicted distribution of y_1 at that age. Uncertainty in projected trajectories was quantified using the same PPS bootstrap framework applied in the primary analyses. These projections represent model-based counterfactual simulations aligned with cross-sectional age gradients and should not be interpreted as observed longitudinal transitions.

3. Results

The Chilean National Health Survey 2016–2017 included 6,233 participants. After restricting the sample to adults aged ≥ 20 years who completed the oral examination, the analytical dataset comprised 5,165 individuals. Sample size varied slightly across specific analyses due to variable-level missingness, particularly for years of schooling and selected chronic condition indicators used in the construction of the composite indices.

3.1. Demographic Characteristics of the Analytical Sample

The analytical sample comprised 5,165 adults aged ≥ 20 years who completed the oral examination. The weighted population represented approximately 11.7 million Chilean adults based on the survey expansion factor (Fexp_F1p_Corr). The mean age of participants was 51.4 years (SD = 17.9), with ages ranging from 20 to 98 years. Women accounted for 51% of the sample and men for 49%. Most individuals resided in urban areas (89.1%), while 10.9% lived in rural areas.

Socioeconomic Vulnerability Index (SVI)

The Socioeconomic Vulnerability Index (SVI) was computed for 4,910 participants (95.1% of the analytic sample) with complete information on all five components. Employment vulnerability was the most prevalent component (41.2%). Educational vulnerability, derived from normalized years of schooling, had a mean value of 0.54 (SD = 0.20), reflecting substantial dispersion in educational attainment across the population.

SVI showed a mean of 0.28 (SD = 0.19), with values ranging from 0 to 1. The distribution was moderately right-skewed, with a median of 0.29 and an inter-quartile range of 0.091–0.355, indicating meaningful heterogeneity in social vulnerability within the study population. Quartile classification demonstrated that 23.9% of participants were in the highest vulnerability quartile, while 25.5% were in the lowest.

The composition and distribution of SVI components are detailed in Table 4.

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Table 4. Components and distribution of the Socioeconomic Vulnerability Index (SVI). ENS, Chile, 2016–2017.

Component	n (sample)	Weighted prevalence / mean
Employment vulnerability (unemployed/economically inactive)	5,093	41.2%
Indigenous vulnerability (self-identified)	5,165	7.7%
Sanitation vulnerability (deficient household sanitation)	5,021	9.9%
Educational vulnerability (normalized years of schooling, 0–1)	5,118	Mean 0.54 (SD = 0.20)
Rural vulnerability (rural residence)	5,165	10.8%
SVI (composite index, 0–1)	4,910	Mean 0.28 (SD = 0.19)

Notes: SVI was computed as the unweighted mean of five components. Educational vulnerability was derived by normalizing years of schooling to a 0–1 scale and reversing direction so that higher values indicate greater vulnerability. Complete-case analysis yielded 4,910 individuals (95.1% of the analytic sample).

Most participants resided in urban areas (89.2%). Marked territorial heterogeneity was observed across macro-regions: just over half of the population resided in the Central macro-region (50.96%), followed by the Central–South (23.4%) and Austral (18.6%) macro-regions, whereas the Northern macro-region accounted for a smaller share (7.0%). Educational attainment ranged from 0 to 22 completed years of schooling, with a mean of 11.0 years (SD = 4.41), reflecting substantial variability in formal education across the population.

3.2. Health-Related Behaviors

Health-related behaviors were assessed to characterize lifestyle exposures in the adult population and to contextualize subsequent analyses of morbidity burden and oral health outcomes. After applying survey expansion factors, 33.4% of adults reported current tobacco use, whereas alcohol consumption during the previous 12 months was reported by 77.3% of the population, indicating a high prevalence of behavioral risk factors in the analytical sample (Table 5).

Table 5. Health-related behaviors of the study population. ENS, Chile, 2016–2017.

Variable	Category / Unit	n (sample)	N (weighted)	%
Current tobacco use	Present	5,165	11,692,408	33.4
Alcohol consumption (last 12 months)	Present	5,023	12,678,675	77.3

Notes: Percentages are population-weighted estimates. Tobacco use was weighted using Fexp_F1p_Corr; alcohol consumption was weighted using Fexp_F2p_Corr, according to ENS module-specific expansion factors.

3.3. Systemic Chronic Conditions

The population-weighted prevalence of chronic conditions indicated a substantial burden of morbidity in the adult population. Obesity (36.7%) and arterial hypertension (30.6%) were the most prevalent conditions, followed by reduced mobility (21.1%) and diabetes mellitus (13.5%).

Self-reported cancer showed a prevalence of 4.6%, although this variable had a higher proportion of missing data and was therefore excluded from the primary construction of the morbidity score (MS).

Taken together, these results reflect a high prevalence of cardio-metabolic and functional conditions, supporting the relevance of modeling cumulative morbidity burden in subsequent analyses (Table 6).

 doi:10.20944/preprints202603.1535.v1

Table 6. Systemic chronic conditions of the study population. ENS, Chile, 2016–2017.

Condition	n (sample)	N (weighted)	Prevalence (%)
Obesity	5,128	13,027,276	36.7
Arterial hypertension	5,157	13,080,025	30.6
Reduced mobility	5,165	11,692,408	21.1
Diabetes mellitus	5,165	13,083,296	13.5
Joint diseases (osteoarthritis)	5,131	12,994,346	7.9
Thyroid disease	5,142	13,056,503	7.6
Depression	5,101	11,574,117	6.7
Liver disease	5,144	13,062,027	5.7
Respiratory diseases (asthma)	5,144	13,048,519	5.1
Cancer	3,213	6,527,715	4.6
Cardiovascular events (AMI)	5,141	11,655,091	3.8
Cardiovascular events (stroke)	5,133	11,649,241	3.0
Joint diseases (rheumatoid arthritis)	5,141	13,022,802	2.4
Coagulation disorders	5,165	13,096,377	2.4
Respiratory diseases (COPD)	5,155	13,080,897	2.1
Chronic renal failure	5,154	13,080,905	1.8

Notes: Conditions are ordered in descending order of weighted prevalence. Estimates are population-weighted using the appropriate ENS 2016–2017 module-specific expansion factors. The sample size (n) corresponds to individuals with non-missing information for each condition after collapsing to one observation per participant. Sample sizes vary due to condition-specific missingness. Cancer presented substantial missing data and was excluded from the primary construction of the morbidity score (MS) but is reported descriptively.

Morbidity Score (MS)

The morbidity score (MS), constructed from 15 chronic conditions, was calculated for 4,890 individuals (94.7% of the analytical sample) with complete information across all components. The unweighted count-based index (range 0–15) showed a mean of 1.81 (SD $\pm$ 1.72), with a median of 1 condition and an observed range from 0 to 10.

When normalized to a 0–1 scale, the mean MS was 0.12 (SD $\pm$ 0.12), with values ranging from 0.000 to 0.667. The distribution was right-skewed: 26.1% of participants had no chronic conditions, 26.4% had one condition, and 47.4% met the definition of multimorbidity ($\geq$ 2 conditions). Higher counts of coexisting conditions were progressively less frequent, with fewer than 5% of individuals presenting five or more conditions.

These results demonstrate a high cumulative burden of chronic disease in the adult population. In subsequent causal analyses, MS was modeled as a continuous exposure (0–1 scale), allowing estimation of dose–response relationships between increasing multimorbidity burden and tooth-loss outcomes through the regression coefficient β_{MS} and population-averaged contrasts derived via g-computation.

Table 7 illustrates the distributional characteristics of SVI and MS across the analytical sample. Both indicators demonstrated substantial inter-individual variability, indicating heterogeneity in socioeconomic conditions and cumulative illness load among the adult population. The variability in socioeconomic vulnerability and cumulative morbidity provides the empirical basis for subsequent causal modeling, where these factors can be considered as continuous exposures for evaluating their impact on tooth-loss severity (y_1) and total tooth loss (y_2) according to a defined target trial emulation framework.

Table 7. Distributional characteristics of the Socioeconomic Vulnerability Index (SVI) and Morbidity Score (MS). ENS, Chile, 2016–2017.

Variable	n	Mean	SD	Median	IQR	Min	Max
SVI	4,910	0.277	$\pm$0.192	0.291	0.091–0.355	0.000	1.000
MS	4,890	0.120	$\pm$0.115	0.067	0.000–0.200	0.000	0.667

Notes: SD, standard deviation; IQR, inter-quartile range. Both SVI and MS are scaled from 0 to 1. Statistics are reported for individuals with complete data on each index. Indices were computed at the individual level without applying survey weights.

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3.4. Sensitivity Analyses of Composite Indices

To evaluate whether the observed associations reflected cumulative constructs rather than dominance by single components, sensitivity analyses were conducted at both the structural and model levels.

3.4.1. Structural Stability: Leave-One-out Analyses

Alternative specifications of each index were constructed by sequentially omitting individual components. For the SVI, exclusion of employment, indigenous status, sanitation, education, or rural residence produced highly correlated indices relative to the original specification (all $r > 0.85$), supporting distributional stability. Exclusion of education resulted in $r = 0.980$, indicating that although education contributed to variance, the overall structure of the index remained stable.

For the MS, exclusion of diabetes yielded $r = 0.978$ with the original index ($N = 4{,}890$). Inclusion of cancer—despite 37.8% missingness—produced $r = 0.992$ but reduced the effective sample to $N = 3{,}037$ (38% reduction). Given this loss of precision and potential selection bias, cancer was excluded from the primary MS specification.

3.4.2. Marginal Contribution of Dominant Components

To determine whether specific components disproportionately drove the associations, models were re-estimated including educational attainment and diabetes mellitus explicitly alongside their respective indices.

In the case of SVI, incorporation of education reduced the coefficient by 69.5%, although a statistically significant residual influence remained. In the MS analysis, inclusion of diabetes reduced the MS coefficient by 30.2%, yet both diabetes and the residual MS term remained statistically significant. These findings indicate that education and diabetes contribute substantially to their respective indices but do not fully account for the cumulative associations observed.

3.4.3. Interaction Between SVI and MS

An interaction term (SVI $\times$ MS) was incorporated to evaluate potential effect modification. The interaction coefficient was negative and statistically significant ($p = 0.022$), indicating antagonistic effects between socioeconomic vulnerability and multimorbidity. The marginal effect of socioeconomic vulnerability diminished with elevated levels of multimorbidity, while the marginal effect of multimorbidity similarly diminished at increased levels of socioeconomic vulnerability. Two mechanisms may account for this antagonistic pattern: first, partial overlap in the causal pathways through which both factors influence outcomes; and second, ceiling or saturation effects, whereby the potential for further deterioration in health outcomes becomes constrained under conditions of extreme cumulative burden.

Collectively, these sensitivity analyses support the structural robustness of both indices and substantiate their interpretation as cumulative exposures in subsequent analyses. Overall, the results confirm that both indices represent coherent cumulative constructs, while recognizing the disproportionate influence of schooling within the SVI and diabetes within the MS. After establishing the structural stability and interpretative limits of the exposure measurements, the subsequent section describes the distribution of oral health outcomes within the analytical sample.

3.5. Oral Health Outcomes

Oral health outcomes were assessed using two complementary measures: an ordinal indicator of tooth-loss severity (y_1) and a continuous measure representing the cumulative number of remaining natural teeth (y_2). Regarding y_1, 72.6% of adults presented functional dentition ($\geq$ 20 remaining teeth), and 5.5% were edentulous. For y_2, the mean number of remaining natural teeth was 21.5 (SD $\pm$ 9.6), with an observed range from 0 to 28 teeth (Table 8).

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Table 8. Oral health outcomes of the study population. ENS, Chile, 2016–2017.

Outcome	Category / Unit	n (sample)	N (weighted)	Mean / %
Tooth-loss severity (y_1)	Functional dentition ($\geq$ 20 teeth)	5,165	13,096,377	72.6
	Moderate tooth loss (10–19 teeth)	5,165	13,096,377	14.4
	Severe tooth loss (1–9 teeth)	5,165	13,096,377	7.5
	Edentulism (0 teeth)	5,165	13,096,377	5.5
Remaining natural teeth (y_2)	Number of teeth	5,165	13,096,377	21.5 (SD $\pm$ 9.6)

Notes: Estimates are population-weighted using the ENS module-specific expansion factor for oral examination data (Fexp_F2p_Corr). Percentages correspond to the distribution of the ordinal severity outcome. The continuous outcome is summarized using the weighted mean and standard deviation.

Figure 2 presents the distribution of remaining natural teeth across age groups, illustrating the life-course gradient in tooth retention within the analytical sample. Median tooth count declined progressively with age, with individuals aged 20–30 years exhibiting near-complete dentition, followed by a gradual reduction in the 31–45 and 46–60 groups. A marked shift was observed from age 61 years onwards, where the median number of remaining teeth fell below the functional dentition threshold (20 teeth). Among participants aged 76 years or older, tooth loss was more advanced, with a high concentration of low tooth counts and edentulism.

This age-stratified pattern supports the cumulative nature of tooth loss and reinforces the biological plausibility of modeling age as a key confounder and potential effect modifier in subsequent causal analyses. While age captures the temporal dimension of cumulative dental loss, it does not account for the structural and clinical determinants that shape differential trajectories across individuals. To contextualize these gradients, we next examine the distribution of key social and morbidity indices within the analytical sample.

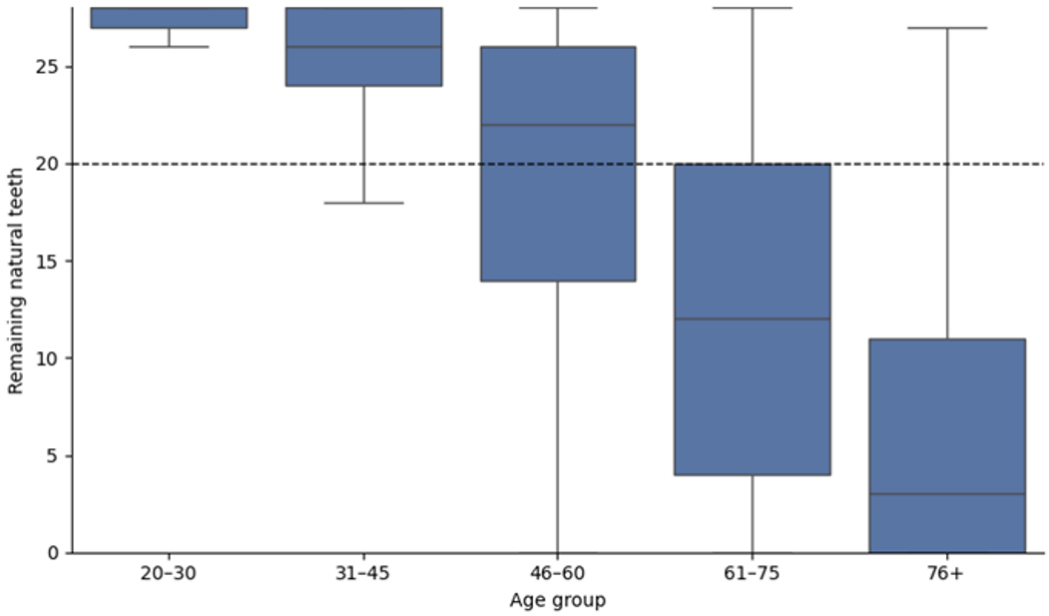

Figure 2. Distribution of remaining natural teeth (y_2) by age group in adults aged $\geq$ 20 years (ENS 2016–2017, $N = 5{,}165$). Box-plots display medians, inter-quartile ranges, and extreme values of tooth counts within each age category (20–30, 31–45, 46–60, 61–75, 76+ years). The dashed horizontal line indicates the functional dentition threshold ($\geq$ 20 teeth). The figure illustrates the progressive decline in tooth retention across the life course.

3.6. Descriptive Associations and Model-Building Rationale

Prior to causal estimation, exploratory analyses were conducted to characterize the conditional-dependence structure among age, SVI, MS, and oral health outcomes. This preliminary step aimed to

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identify relevant statistical associations, inform co-variate selection for subsequent causal models, and detect potential effect modification. These descriptive patterns do not constitute causal claims; formal causal inference is presented in subsequent sections after appropriate adjustment for confounding.

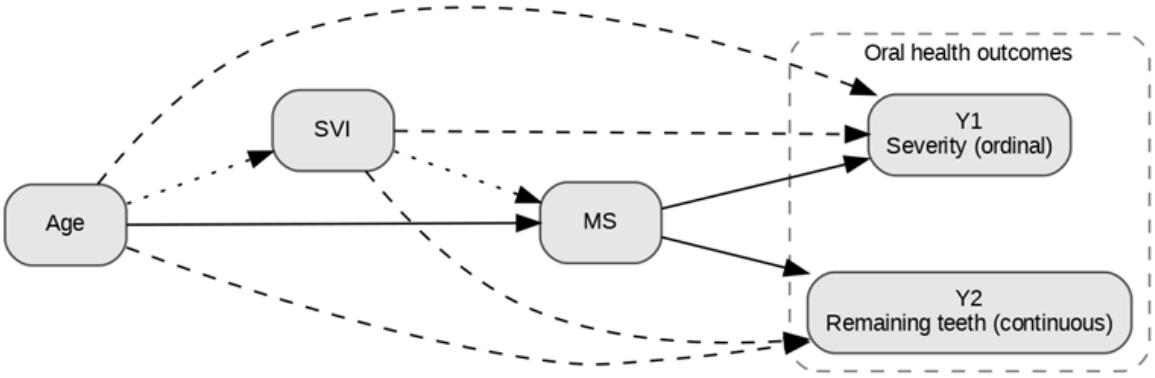

Figure 3. Exploratory conditional-dependence graph among age, socioeconomic vulnerability (SVI), multimorbidity (MS), and oral health outcomes. Line types indicate the relative strength of observed conditional associations (solid: stronger; dashed: moderate; dotted: weaker). Y_1 denotes ordinal tooth-loss severity and Y_2 the number of remaining natural teeth (continuous). This representation characterizes descriptive statistical patterns and does not establish causal relationships. A significant negative interaction between SVI and MS ($\beta_{\text{SVI}\times\text{MS}} = -0.237$, $p = 0.022$) was detected in subsequent sensitivity analyses, indicating non-additive effects. Causal effect estimates are presented in the following sections after appropriate adjustment for confounding.

3.7. Causal Effects of Social Vulnerability and Multimorbidity on Tooth Loss

We estimated independent causal effects of SVI and MS using confounder-adjusted regression models followed by weighted g-computation with probability-proportional-to-size bootstrap (1,000 replications).

3.7.1. Conditional Effects

In the proportional-odds model for y_1, higher SVI was strongly associated with worse clinical categories (OR = 7.86; 95% CI: 7.85–20.11 per unit increase). MS was also independently associated with greater severity (OR = 5.31; 95% CI: 1.84–11.56). Because both indices are scaled from 0 to 1, these odds ratios correspond to the full observed exposure range and should be interpreted as reflecting strong monotonic gradients across the vulnerability and multimorbidity continua.

For y_2, both exposures were associated with fewer remaining teeth. Each unit increase in SVI was associated with -5.99 teeth (95% CI: -6.17 to -4.03), and each unit increase in MS with -6.14 teeth (95% CI: -10.46 to -5.29), after adjustment.

3.7.2. Population-Averaged Effects (P25 $\rightarrow$ P75)

To obtain population-level causal contrasts under realistic exposure shifts, we estimated average treatment effects (ATEs) comparing the 25th and 75th percentiles of each exposure distribution. For SVI, an increase from 0.091 to 0.345 was associated with a 0.093-point increase in ordinal tooth-loss severity (95% CI: 0.072–0.104) and a reduction of 1.52 remaining teeth (95% CI: -1.57 to -1.03).

For MS, an increase from 0.00 to 0.20 was associated with a 0.059-point increase in ordinal severity (95% CI: 0.015–0.064) and a reduction of 1.23 remaining teeth (95% CI: -2.09 to -1.06). Across both outcomes, SVI demonstrated slightly larger population-averaged effects than MS, indicating that upstream socioeconomic vulnerability may exert a broader influence on tooth-loss burden, independent of chronic disease accumulation. All ATEs were estimated using weighted g-computation with probability-proportional-to-size bootstrap (1,000 replications), ensuring consistency with the survey expansion factor for dental outcomes.

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Table 9. Population-Averaged Causal Effects (PPS bootstrap, $n = 1{,}000$).

Exposure	Outcome	Contrast (P25 → P75)	ATE	95% CI Lower	95% CI Upper
SVI	y_1 (severity)	0.091 → 0.345	0.093	0.072	0.104
MS	y_1 (severity)	0.000 → 0.200	0.059	0.015	0.064
SVI	y_2 (teeth)	0.091 → 0.345	−1.52	−1.57	−1.03
MS	y_2 (teeth)	0.000 → 0.200	−1.23	−2.09	−1.06

Notes: Average treatment effects (ATEs) were estimated using weighted g-computation. Ninety-five per cent confidence intervals were obtained via probability-proportional-to-size (PPS) bootstrap with 1,000 replications. All models were adjusted for age, sex, tobacco use and alcohol consumption. Both SVI and MS were normalized to a 0–1 scale prior to estimation.

3.8. Age-Conditional Counterfactual Trajectories of Tooth-Loss Severity

To translate the estimated causal effects into clinically interpretable age-dependent risk profiles, we derived age-conditional counterfactual trajectories of tooth-loss severity from the fitted proportional-odds model. Tooth-loss severity was represented using four ordered clinical states: functional dentition (S_0), moderate tooth loss (S_1), severe tooth loss (S_2), and edentulism (S_3). Rather than modeling observed longitudinal transitions, predicted outcome probabilities were evaluated across increasing ages while holding determinant profiles constant, yielding age-conditional projections under sustained exposure scenarios.

For each baseline age (35, 45, and 60 years), the probability of edentulism ($y_1 = S_3$) was computed over a 40-year horizon by incrementing age within the fitted ordinal model while fixing exposure profiles. Favorable and unfavorable realistic scenarios were defined empirically using the 25th and 75th percentiles of SVI and MS, respectively, with sex, tobacco use, and alcohol consumption fixed at reference categories. This approach provides a transparent mapping from determinant profiles to age-conditional severity risks without invoking assumptions about underlying transition intensities.

Across all baseline ages, unfavorable profiles were associated with systematically higher predicted probabilities of edentulism than favorable profiles. At a baseline age of 35 years, the predicted probability of edentulism by age 100 was approximately 0.69 under favorable conditions and 0.85 under unfavorable conditions, corresponding to an absolute difference of 0.15. For individuals starting at 45 years, the corresponding probabilities were approximately 0.64 (favorable) and 0.98 (unfavorable), yielding a larger absolute separation at advanced ages. Among those beginning at 60 years, predicted probabilities rose more steeply, approaching unity under unfavorable conditions by late life and remaining elevated even under favorable profiles.

At intermediate target ages, contrasts were also clinically meaningful. For example, at age 90, the absolute difference between unfavorable and favorable profiles exceeded 0.20 across baseline strata, indicating a substantial shift in the population-level risk of complete tooth loss attributable to sustained adverse determinant conditions. The widening separation with increasing age reflects cumulative amplification of risk under fixed high-vulnerability and high-multimorbidity profiles.

Baseline age functioned as a structural modifier of predicted risk: individuals entering the projection at 60 years exhibited markedly higher probabilities throughout the time horizon than those starting at 35 or 45 years under identical determinant profiles. These findings are consistent with the non-linear age gradient estimated in the underlying ordinal model and reinforce the interaction between chronological aging and sustained social and systemic risk exposure.

Figure 4a–c illustrate the age-dependent likelihood of edentulism ($y_1 = S_3$) over a 40-year period, stratified by baseline age and counterfactual determinant profile. Shaded areas represent 95% bootstrap confidence intervals derived from a probability-proportional-to-size resampling procedure aligned with the survey expansion factors. These trajectories correspond to model-derived, age-conditional projections under fixed exposure scenarios and should not be interpreted as observed longitudinal transitions. Absolute differences between favorable and unfavorable profiles were substantial across all age groups, whereas relative differences diminished at extreme ages as projected probabilities approached their upper bounds, consistent with the logistic functional form of the proportional-odds

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model. Collectively, these results illustrate how regression-based causal estimates can be translated into age-dependent risk trajectories while remaining consistent with the underlying cross-sectional design.

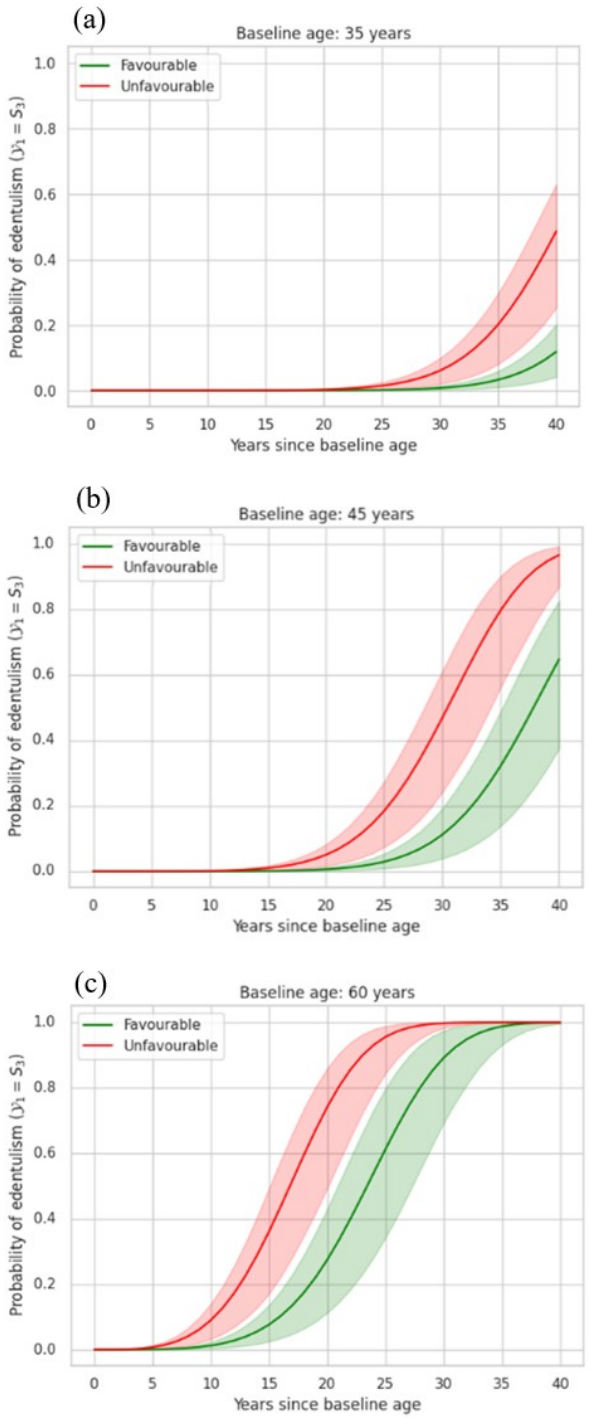

Figure 4. Age-conditional Markov projection of edentulism ($y_1 = S_3$) for a baseline age of a) 35, b) 45 and c) 60 years. Trajectories compare favorable and unfavorable exposure profiles defined by the 25th and 75th percentiles of the Social Vulnerability Index (SVI) and Multimorbidity Score (MS), respectively. Shaded areas represent PPS bootstrap 95% confidence intervals ($B = 1{,}000$).

4. Discussion

This population-based causal analysis of 5,165 Chilean adults provides robust evidence regarding the independent effects of socioeconomic vulnerability (SVI) and cumulative multimorbidity burden

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(MS) on tooth-loss severity (y_1) and the number of remaining natural teeth (y_2). In fully adjusted proportional-odds models, a one-unit increase in SVI (0–1 scale) was associated with an odds ratio of 7.86 for transition to a more severe tooth-loss category, whereas MS showed an odds ratio of 5.31. For the continuous outcome, a one-unit increase in SVI was associated with a reduction of 5.99 teeth, and a one-unit increase in MS with a reduction of 6.14 teeth after adjustment for age, sex, tobacco use, and alcohol consumption. Because both indices are scaled from 0 to 1, these coefficients represent gradients across the full observed exposure range.

Population-averaged contrasts obtained through weighted g-computation facilitate interpretation at the distributional level. An increase in SVI from the 25th to the 75th percentile (0.091 to 0.345) was associated with a 0.093-point increase in ordinal severity and a reduction of 1.52 remaining teeth. A comparable shift in MS (0.00 to 0.20) was associated with an increase in severity of 0.059 points and a reduction of 1.23 teeth. Across both outcomes, SVI exhibited slightly larger population-averaged effects than MS, suggesting that socioeconomic vulnerability may exert a broader influence on tooth-loss burden than the accumulation of chronic diseases.

Sensitivity analyses assessed the structural stability of both indices. Leave-one-out procedures showed high correlations between alternative and primary SVI specifications (all $r > 0.85$) and between the primary MS and the specification excluding diabetes ($r = 0.978$). Including cancer in the MS yielded $r = 0.992$ but substantially reduced the effective sample size; cancer was therefore excluded from the primary specification to preserve statistical precision.

Model-level sensitivity analyses examined the influence of specific components within each index. When educational attainment was explicitly included alongside SVI, the SVI coefficient decreased by 69.5% but remained statistically significant, indicating that education explains a substantial portion of the SVI effect without fully accounting for it. Similarly, when diabetes was included explicitly alongside MS, the MS coefficient decreased by 30.2%, while both variables remained statistically significant. These findings suggest that the observed relationships are not driven by a single component within either index.

A statistically significant negative interaction between SVI and MS ($p = 0.022$) was observed. The marginal effect of SVI decreased at higher levels of MS, and the marginal effect of MS decreased at higher levels of SVI, consistent with partial overlap in their contributions to tooth-loss severity.

Regression-based estimates were further translated into age-conditional trajectories of edentulism ($y_1 = S_3$) using a non-homogeneous, age-dependent Markov extension of the fitted ordinal model. Under sustained unfavorable exposure profiles (75th percentiles of SVI and MS), projected probabilities of edentulism increased more rapidly with age than under favorable profiles (25th percentiles). These projections reflect model-derived age gradients calibrated to cross-sectional data and should not be interpreted as observed longitudinal transitions.

Overall, the consistency of results across regression models, g-computation contrasts, structural sensitivity analyses, component-specific re-estimation, interaction testing, and age-conditional projections supports the internal coherence of the analytical framework and the stability of the primary findings.

Our findings align with prior evidence documenting socioeconomic gradients in tooth loss [1,4,16,32], though the measurement scale and operationalization of exposures differ substantially across studies, our approach differs by modeling socioeconomic disadvantage as a composite index rather than as isolated indicators. Instead of analyzing individual socioeconomic variables separately, we constructed a Social Vulnerability Index (SVI) scaled continuously from 0 to 1. Within this framework, a complete shift across the SVI range corresponded to an odds ratio of 7.86 for progression to a more severe tooth-loss category and a mean reduction of 5.99 remaining teeth. When expressed through inter-quartile contrasts (P25 versus P75), the corresponding population-averaged reduction of 1.52 teeth falls within the range of clinically meaningful differences reported in population-based studies, while reflecting cumulative structural disadvantage rather than isolated socioeconomic markers.

 doi:10.20944/preprints202603.1535.v1

The substantially larger gradients observed in the present study likely stem from three methodological distinctions. First, the SVI simultaneously captures multiple structural dimensions—including educational attainment, employment status, sanitation infrastructure, indigenous ethnicity, and geographical area of residence—within a unified exposure construct. Second, exposures were modeled on a continuous scale, thereby preserving dose–response information across the entire distribution rather than relying on binary or categorical contrasts. Third, causal contrasts were estimated using inverse probability-weighted g-computation with percentile-preserving stratified (PPS) bootstrap resampling, yielding distributional-level estimates under explicit percentile shifts rather than conventional regression coefficients alone.

These distinctions suggest that the magnitude of the observed gradients reflects the cumulative configuration of structural vulnerability across domains rather than the effect of isolated socioeconomic characteristics.

Santos-López et al. (2024) [12] recently reported an odds ratio (OR) of 1.66 (95% confidence interval [CI]: 1.04–2.66) for severe tooth loss among adults aged $\geq$ 65 years with two or more chronic conditions when analyzing the same ENS 2016–2017 dataset. The present study demonstrates a comparable association between multimorbidity and tooth loss (OR = 1.94 per one-unit increase on the 0–1 morbidity scale), although important methodological differences should be noted. The conventional approach, as exemplified by Santos-López et al., operationalizes multimorbidity as a simple count of chronic diseases. This binary or categorical specification does not fully capture the cumulative risk arising from the co-occurrence of multiple chronic conditions. In contrast, the morbidity index used here is scaled continuously, reflecting progressive disease burden across the entire distribution.

Moreover, the finding that the inclusion of diabetes led to a 30.2% attenuation of the multimorbidity coefficient provides evidence that diabetes functions as a key mediating pathway linking multimorbidity to tooth loss. This observation is consistent with the well-established causal role of diabetes in the progression of periodontal disease [17,33], suggesting that a significant proportion of the effect of multimorbidity on tooth loss operates through periodontal health.

Whilst longitudinal associations between tooth loss and chronic conditions are extensively documented [3,5,7,12,15,23,34,35], formal causal evidence remains limited, particularly in middle-income settings. Recent methodological advances include Kiuchi et al. (2022) [14] fixed-effects analysis of oral status and cognitive decline, and Baumeister et al. (2025) [24] instrumental variable approach to estimating smoking effects on tooth loss. Our study extends this emerging causal literature by: (1) focusing on upstream structural social determinants of health and multimorbidity rather than individual behaviors; (2) providing population-representative estimates from a nationally representative middle-income country survey; (3) explicitly defining target estimands within a potential outcome framework; and (4) translating causal effects into clinically interpretable age-conditional risk trajectories.

The large protective effect of educational attainment operates through multiple interconnected life-course pathways. Education shapes oral health literacy and preventive behaviors from early life, influencing knowledge about caries prevention, periodontal disease, and the importance of routine dental care. Employment status—itself strongly correlated with education—determines income, health insurance coverage, and capacity to afford dental treatment in Chile's mixed public-private healthcare system. Rural residence is associated with markedly reduced availability of dental services and greater geographical barriers to access [16]. The irreversibility of tooth loss means that disadvantages accumulating across these domains have permanent consequences, with limited opportunity for reversal even if circumstances later improve.

Systemic morbidity affects tooth loss through both biological and behavioral pathways. Chronic diseases generate systemic inflammation that exacerbates periodontal tissue destruction and impairs wound healing [17,33,36]. Diabetes specifically causes metabolic dysregulation, compromising immune function and increasing susceptibility to oral infections [23,37]. Medications used in the management of chronic conditions—particularly antihypertensives, antidepressants, and immuno-

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suppressants—frequently cause xerostomia, reducing saliva's protective antimicrobial and buffering effects and thereby increasing the risk of caries and periodontal disease [23,33].

Beyond these direct biological mechanisms, multimorbidity may also reduce the capacity for oral self-care through functional limitations, depression-related neglect of hygiene, and mobility constraints affecting access to dental services. Moreover, individuals with limited resources may prioritize management of life-threatening systemic conditions over oral health, creating a "competing demands" dynamic that relegates preventive dental care. Our finding that diabetes accounts for 30.2% of the morbidity effect, while substantial residual effects remain, indicates that integrated chronic disease management addressing both diabetes control and oral health maintenance may be necessary but insufficient; the broader burden of multimorbidity must also be considered.

A significant methodological innovation of this analysis is the conversion of regression-based causal estimates into age-conditional edentulism trajectories. While odds ratios measure relationships on a relative scale, absolute risk trajectories provide clinically interpretable representations of population-level burden and illustrate the accumulation of effects across the life course. By evaluating model predictions across increasing ages under sustained favourable versus unfavourable exposure conditions, we observed substantial divergence: individuals with high social vulnerability and multimorbidity exhibited an estimated cumulative risk of edentulism of approximately 75–80% by age 75, compared with roughly 25–30% among those with low vulnerability and morbidity. These projections should be interpreted as pseudo-temporal representations of effect magnitude rather than predictions of individual outcomes, as they rely on cross-sectional age gradients and assume constant exposure conditions that do not fully represent real-world dynamics. Nevertheless, they clearly illustrate that population-level prevention requires early and sustained intervention to prevent cumulative disadvantage, rather than focusing exclusively on late-stage disease in older adults.

This study has several important strengths. The ENS 2016–2017 provides nationally representative data with extensive measurement of sociodemographic, behavioural, and clinical characteristics, allowing adjustment for a broad set of potential confounders. Our explicit causal framework, grounded in the potential outcomes approach and target trial emulation, enables more transparent inference than conventional observational analyses by clearly defining assumptions, estimands, and comparison strategies. The use of continuous composite indices preserves dose–response information that is often lost in categorical analyses. G-computation provides population-averaged causal effects that are directly relevant for public health planning, complementing conditional estimates derived from regression models. Sensitivity analyses confirmed the robustness of findings across alternative model specifications. In particular, the analyses identified diabetes as a key mechanism linking multimorbidity to tooth loss. Finally, translating causal estimates into age-conditional trajectories enhances clinical and policy interpretability.

Several limitations should also be acknowledged. First, the cross-sectional design prevents direct observation of temporal sequence, limiting causal inference despite the application of methods designed to mitigate this constraint. Although social vulnerability components and multimorbidity plausibly precede tooth loss—and tooth loss itself is largely irreversible—we cannot completely exclude reverse causation (e.g., tooth loss affecting employment or contributing to depression). Longitudinal follow-up of ENS participants would strengthen causal inference. Second, unmeasured confounding remains possible. The ENS lacks detailed information on oral hygiene behaviors, which are important determinants of dental caries and periodontitis, both of which lead to tooth loss. Nevertheless, the SVI may partially capture this unmeasured dimension, given the established association between educational attainment, health literacy, and preventive behaviors. Third, tooth loss was assessed by trained nurses rather than dentists; however, high inter-rater reliability ($\kappa = 0.85$) and the use of simple presence/absence assessment reduce concerns regarding measurement error. Fourth, self-reported chronic conditions may underestimate true prevalence, potentially biasing morbidity effects toward the null. Finally, the findings may not be fully generalizable beyond Chile, as social determinants

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and health system structures vary across settings, although the biological mechanisms linking chronic disease and periodontal health are likely broadly applicable [33,38,39].

These findings have direct implications for oral health policy in Chile and in comparable middle-income settings. Chilean oral health policy has historically prioritized individuals under 20 years of age, leaving adults over 20 years—except pregnant women and those aged 60 years with GES coverage—largely restricted to emergency care services [16,18,22,39]. This prioritization pattern may have contributed to the substantial burden of disease documented in this study, with 27.4% of adults presenting moderate to severe tooth loss or edentulism. The 2020 *Estrategia de Cuidado Integral Centrado en las Personas (ECICEP)* [21]—a shift toward person-centred chronic disease management for individuals aged 15 years and older—represents an important opportunity for integration. However, the ECICEP operational framework marginalizes oral health because, although it incorporates a wide range of general and mental health conditions, it does not explicitly include caries or periodontitis, despite their high prevalence as non-communicable diseases. Consequently, oral health remains peripheral within the strategy, even though it is formally recognized as a component of adult health. A notable positive element of this policy is the inclusion of periodontal treatment for individuals aged 35–54 years with uncontrolled diabetes, together with the development of dental risk assessment guidelines for adults aged 20 years and older.

The cumulative disadvantage framework emphasizes that policies aimed at improving and maintaining oral health must incorporate upstream interventions addressing structural determinants of health, including educational attainment and labor conditions. In addition, the development of a comprehensive continuum of oral health care—integrating risk stratification based on a social vulnerability index within routine adult care—has the potential to modify tooth-loss trajectories at the population level. Such an approach would allow targeted allocation of resources to individuals facing the greatest structural barriers to maintaining oral health, thereby addressing inequalities at their source.

At a second level of intervention, public policies designed to improve oral health should include: (1) ensuring access to dental check-ups and preventive services, currently provided free of charge in primary health care centers for patients aged 6 months to 19 years; (2) formally integrating oral health assessment within the ECICEP operational framework; (3) expanding conservative and restorative dental coverage for adults aged 20–59 years; (4) strengthening the oral health care network through university-based training clinics and community outreach programs capable of expanding service capacity while providing supervised clinical training; (5) improving access to preventive and restorative services in rural and geographically isolated areas through mobile dental units and remote dentistry platforms; (6) developing partnerships with Indigenous communities to co-design culturally appropriate oral health services that address structural barriers; and (7) establishing integrated data systems linking oral health indicators with chronic disease registries to facilitate monitoring of inequalities and evaluation of integrated care models.

Future research should prioritize longitudinal designs following ENS cohorts to strengthen causal inference, pragmatic trials testing integrated chronic disease and oral health interventions, formal causal mediation analyses elucidating specific biological and behavioral pathways, investigations of effect heterogeneity across age, sex, and regional subgroups, and economic evaluations of upstream prevention strategies. Comparative studies across Latin American countries would enhance understanding of context-dependent social determinants.

5. Conclusions

This study provides population-level causal evidence that cumulative tooth loss in Chilean adults is independently influenced by structural social vulnerability and systemic multimorbidity. With explicit causal assumptions and nationally representative data, both exposures revealed consistent gradients across ordinal severity and remaining tooth count, with socioeconomic vulnerability having slightly higher effects on distribution than multimorbidity burden. Population-averaged contrasts

 doi:10.20944/preprints202603.1535.v1

indicated that realistic changes in exposure distribution (P25→P75) corresponded with clinically significant decreases in tooth retention. Furthermore, age-conditional Markov projections demonstrated a continuous increase in absolute inequalities in edentulism probability under persistent adverse exposure profiles, highlighting the accumulation of structural and clinical disadvantages throughout the lifespan. Despite the decrease of relative contrasts at extreme ages due to model limitations, the separation of absolute risk remained significant. These findings indicate that tooth loss cannot be primarily attributed to aging or personal habits. Instead, it represents the aggregate arrangement of preceding socioeconomic factors and persistent health issues. In aging middle-income cultures marked by enduring structural disparities and a high prevalence of multimorbidity, alleviating the burden of tooth loss necessitates comprehensive measures that tackle both social vulnerability and chronic disease care throughout adulthood. In the absence of upstream action, cross-sectional gradients are likely to result in persistent inter-generational inequalities in oral health.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

Author Contributions: JJ conceived and designed the study, oversaw the investigation, developed the methodological framework and causal analysis strategy, conducted the data analysis and software implementation, and drafted the original manuscript. JJ also coordinated manuscript revisions and serves as the corresponding author. MB contributed to the conceptualization of the study and the methodological design, participated in data analysis, assisted in manuscript preparation, and critically reviewed and revised the final version. KC contributed to data investigation and validation, drafted relevant sections of the manuscript, and reviewed and refined the text to ensure conceptual consistency and intellectual rigor. PM reviewed and validated the results, contributed to writing and editing the manuscript for methodological precision and conceptual clarity, developed and implemented the analytical software procedures, and participated in the statistical analysis of the data. XC provided oversight of the methodological framework and analytical strategy, supervised the preparation of the manuscript, and critically reviewed the text to ensure conceptual clarity, methodological rigor, and scientific coherence. MG contributed to the methodological design of the study, provided academic oversight of the analytical framework, and critically evaluated the manuscript to ensure methodological rigor and conceptual consistency. AV formulated the causal inference framework, contributed to the methodological design of the causal analysis, participated in data analysis and interpretation, and conducted a comprehensive critical revision of the manuscript to ensure coherence of the causal approach and overall scientific integrity.

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Informed Consent Statement: Not applicable.

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Abbreviations

The following abbreviations are used in this manuscript:

AMI	Acute myocardial infarction
ATE	Average treatment effect
BMI	Body mass index
CI	Confidence interval
COPD	Chronic obstructive pulmonary disease
DAG	Directed acyclic graph
ECICEP	Comprehensive Person-Centered Care Strategy
ENS	Chilean National Health Survey
Fexp_EX1p_Corr	Survey expansion factor (module EX1)
Fexp_F1F2p_Corr	Combined survey expansion factor (modules F1 and F2)
Fexp_F1p_Corr	Survey expansion factor (module F1)
Fexp_F2p_Corr	Survey expansion factor (module F2)
GES	Explicit Health Guarantees
IQR	Inter-quartile range
MS	Multimorbidity Score
NA	Not available
OR	Odds ratio
P25	25th percentile
P75	75th percentile
PPS	Probability-proportional-to-size
SD	Standard deviation
SVI	Socioeconomic Vulnerability Index

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