Impact of teeth on social participation: modified treatment policy approach

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Abstract

Social participation prevents social isolation and loneliness among older adults while having numerous positive effects on their health and well-being in rapidly aging societies. We aimed to estimate the effect of retaining more natural teeth on social participation among older adults in Japan. The analysis used longitudinal data from 24,872 participants in the Japan Gerontological Evaluation Study (2010, 2013, and 2016). We employed longitudinal modified treatment policy approach to determine the effect of several hypothetical scenarios (preventive scenarios and tooth loss scenarios) on frequent social participation (1=at least once a week/ 0= less than once a week) after a six-year follow-up. The corresponding statistical parameters were estimated using targeted minimum loss-based estimation (TMLE) method. Number of teeth category (edentate/1-9/10-19/≥ 20) was treated as a time-varying exposure, and the outcome estimates were adjusted for time-varying (income, self-rated health, marital status, IADL, vision loss, hearing loss, major comorbidities, and number of household members) and time-invariant covariates (age, sex, education, baseline social participation). Less frequent social participation was associated with older age, male sex, lower income, low educational attainment, and poor self-rated health at the baseline. Social participation improved when tooth loss prevention scenarios were emulated. The best preventive scenario (i.e., maintaining ≥ 20 among each participant) improved social participation by 8% (Risk Ratio [RR]= 1.08, 95%CI=1.05,1.11). Emulated tooth loss scenarios gradually decreased social participation. Hypothetical scenario in which all the participants were edentate throughout the follow-up period resulted in a 11% (RR= 0.89, 95%CI=0.84,0.94) reduction in social participation.

Subsequent tooth loss scenarios showed 8% (RR= 0.92, 95%CI=0.88,0.95), and 6% (RR= 0.94, 95%CI=0.91,0.97), and 4% (RR= 0.96, 95%CI=0.93,0.98) reductions, respectively. Thus, among Japanese older adults, retaining a higher number of teeth positively affects their social participation, whereas being edentate or having a relatively lower number of teeth negatively affects their social participation.

Introduction

The term “social participation” refers to an individual’s involvement in activities that allow them to interact with others in their community or society in general (Levasseur et al. 2010). Social participation among older adults is an essential component of healthy ageing because it has numerous positive effects on both individuals and society (Golinowska et al. 2016). With increasing population aging older adults’ participation in social activities is becoming a key element to prevent social isolation (WHO 2018). Hence, it is important to consider when formulating ageing-friendly policies. Previous studies have linked higher levels of social participation to higher life expectancy, lower cognitive decline, well-being, and functioning of older adults (Hikichi et al. 2016; Wanchai and Phrompayak 2018). Community-level health promotion and prevention activities such as physical activity, smoking and alcohol interventions, could also be facilitated through social engagement (Saito et al. 2019). A wide range of determinants, including health-related factors, influence older adults’ level of social participation (Cornwell and Waite 2009; Zhang et al. 2020).

Teeth are important in different aspects of daily life, such as eating, speaking, smiling, and making facial expressions, all of which are essential for positive social interactions. Tooth loss is highly prevalent among older adults due primarily to a life-long accumulation of chronic dental conditions such as dental caries and periodontal diseases (Bernabe et al. 2020). Previous studies have consistently linked social and neighbourhood related factors such as social capital and social participation to oral health related outcomes among older adults (Aida et al. 2011; Takeuchi et al. 2013;

Rouxel et al. 2015). Much less is known about the effect of oral health on participation in social activities.

The World Health Organization (WHO) recommends that older adults should have at least 20 occluding teeth, also known as “minimal functioning dentition”, to maintain proper oral function (WHO 2013). This criterion can be used as a benchmark to assess the effect of teeth on social participation among older adults. One way to achieve this is by contrasting the amount of observed social participation against the social participation estimates when participants reach closer to or move away from the minimal functional dentition standard. The longitudinal modified treatment policy (LMTP), a novel non-parametric causal inference approach, can be adapted to obtain such contrasts by emulating multiple hypothetical number of teeth scenarios that mimic tooth loss prevention (i.e., reaching towards the benchmark level) and tooth loss (i.e., moving away from the benchmark level) (Díaz et al. 2021; Ikeda et al. 2022).

The literature for causal inference based on binary exposures is extensive (Höfler 2005). However, dichotomisation of the exposure using an arbitrary cut-off point leads to loss of information on the exposure and hinders the ability to observe any “dose-response” effect on the outcome. LMTP, on the other hand, allows us to quantify the effect of a treatment that changes the observed level of exposure in each individual to a new level (Díaz et al. 2021). In other words, this framework can be adapted to quantify counterfactual outcomes for questions such as, “What would happen to the prevalence of social participation if everyone in the study population increased or decreased their number of teeth by a certain amount?”. Furthermore, the corresponding statistical parameters for LMTP can be estimated using doubly-robust statistical estimators, such as the targeted minimum loss-based estimation (TMLE), avoiding strict parametric modelling assumptions (Schuler and Rose 2016; Laan and Rose 2018).

The study aimed to determine the impact of the number of remaining teeth on the social participation of older Japanese adults over a six-year period, while accounting for the time-dependent nature of the variable associations.

Methods

Data

Data from the Japan Gerontological Evaluation Study (JAGES) were used in this analysis (Kondo et al. 2018). JAGES is an ongoing cohort study for over-65 community-dwelling older adults living across 24 urban and suburban municipalities in Japan. In the baseline (2010), 95,827 postal survey questionnaires were randomly distributed within participating municipalities, and 62,418 people responded (response rate: 65.1%). Out of them, only 52,053 participants were functionally dependent and had valid information about their follow-up status. For this analysis, data from 24,872 individuals who participated in the baseline and two subsequent surveys (2013 and 2016) were included. During the six years of follow-up 4611 people died, 8099 became functionally dependent, and 14,471 were lost to follow-up due to other reasons (study flow chart in Figure 1).

Outcome variable

The outcome of this study was social participation in 2016. JAGES recorded the frequency of social participation (“nearly every day”, “twice or thrice a week”, “once a week”, “once or twice a month”, “a few times/year”, “never”) for various social activities.

We assessed the frequency of participation in any of the following activities: hobby groups, sports clubs, senior citizens' clubs, residence groups, or volunteer groups. Participation in any of the aforementioned activities once a week or more frequently was defined as indicative of frequent social participation (1=participation, 0=non-participation). To assess the robustness of the cutoff, a sensitivity analysis was conducted (Appendix Table 1) using once a month or more frequently as the cutoff to define the outcome (Shiba et al. 2021).

Exposure

The number of remaining natural teeth at the time of the surveys in 2010 and 2013 was used as a time-varying exposure. The self-reported number of teeth category was recorded using the response to the question, "How many natural teeth do you currently have?". The response options were 20 or more , 10-19 , 1-9 , no teeth. The "20 or more teeth" category was indicative of having a minimal functioning dentition. The 10-19 teeth category was intended to represent the initial stages of losing minimal functioning dentition and the 1-9 teeth and edentate categories indicate stages of severe tooth loss (Kassebaum et al. 2014).

Covariates

Because the number of teeth was evaluated as a time-varying exposure in this study, both time-invariant and time-variant covariates were taken into account. Age at the baseline (65-99 years), sex, years of formal education (6/ 6-9/ 10-12/ 13 or more), and social participation in 2010 (outcome at baseline) were adjusted for as time-invariant covariates. Equalised annual household income (million yen), self-rated health (very good/ good/ fair/ poor), Instrumental Activities of Daily Living (IADL) score (0-13), vision loss (yes/no), hearing loss (yes/no), cancer (yes/no), heart disease (yes/no), stroke (yes/no), number of household members (1/2/3/4/5/6 or more), and marital status (married/ single, widowed or divorced) were included as time-varying covariates.

Statistical analysis

Hypothesised associations between variables are shown in the directed acyclic graph in Appendix Figure 1. A descriptive analysis was performed to identify the characteristics of participants stratified by outcome. Then, to specify the impact of number of teeth on social participation, the observed number of teeth of each individual at each time point was shifted to new levels to emulate four tooth loss prevention scenarios and four tooth loss scenarios using LMTP framework. Specifically, following hypothetical scenarios were evaluated. Scenarios for the prevention of tooth loss (S1-S4, see the Figure 2);

1. "What if edentate participants had retained at least 1-9 teeth"
2. "What if edentate retained 1-9 teeth and participants with 1-9 retained 10-19 teeth"
3. "What if edentate retained 1-9 teeth and participants with 1-9 retained 10-19 teeth and participants with 10-19 teeth retained ≥ 20 teeth"
4. "What if all participants had retained ≥ 20 teeth"

Tooth loss scenarios (S5-S8, see the Figure 2);

5. "What if participants with ≥ 20 teeth became 10-19 teeth"

6. “What if participants with ≥ 20 teeth became 10-19 teeth and participants with 10-19 teeth became 1-9 teeth”

7. “What if participants with ≥ 20 teeth became 10-19 teeth and participants with 10-19 teeth became 1-9 teeth and participants with 1-9 became edentate”

8. “What if all participants became edentate”

Figure 2 illustrates how the observed level of exposure was shifted to emulate the above exposure scenarios. Furthermore, Appendix Figure 2 shows how these scenarios were emulated in a longitudinal setting.

TMLE was used to estimate the level of social participation with the shifted and the observed exposures (Díaz et al. 2021). In TMLE, the probabilities of the exposure conditional on the covariates (exposure model) and the conditional probabilities of the outcome given the exposure and covariates (g-computation/outcome model) were estimated. Then, to obtain unbiased estimation of the counterfactual outcomes, g-computation estimates were updated using negative inverse probability weights derived from the propensity score model (Schuler and Rose 2016). Therefore, if either the exposure model or the outcome model was consistently estimated, unbiased estimates could be obtained (Laan and Gruber 2012). To increase the likelihood of robust specification of exposure and outcome models, Super Learner algorithms was used (Schomaker et al. 2019). Within the Super Learner, generalised linear models (*glm*), generalised additive models (*gam*), and extreme gradient boosting models (*xgboost*) were used. Additional information regarding the usage of Super Learner in this analysis is provided in the Appendix Text box 1.

Finally, the estimates of each emulated hypothetical scenario were contrasted against the outcome estimate under the observed exposure to calculate risk ratios (RR) and 95% confidence intervals (95% CI) for each respective scenario. All estimates were appropriately controlled for above-mentioned time-variant and time-invariant covariates. In addition, estimates were accounted for attrition of the study population (Lendle et al. 2017). A comparison of baseline characteristics by participants' follow-up status is reported in Appendix Table 2. Furthermore, corresponding E-values were calculated for each RR estimate to report the potential impact of unmeasured confounders (VanderWeele and Ding 2017). Finally, a supplementary logistic regression analysis using baseline exposure and covariates was conducted to assess the difference in estimates using the traditional method and the counterfactual based LMTP approach (Appendix Table 3).

Random forest based multivariate imputation by chained equations (MICE) was used to impute missing data (Buuren and Groothuis-Oudshoorn 2011). Random forest MICE has been shown to produce less biased parameter estimates compared to parametric MICE (Shah et al. 2014). Analyses were performed using five imputed datasets and the estimates were pooled using Rubin's rules (Rubin 2004). Percentages of missingness for each covariate are shown in Appendix Figure 3 and 4. The *lmtp* R package was used to emulate exposure scenarios and to compute TMLE estimates (Williams and Díaz 2020). All R codes used to generate our results can be found at *https://github.com/upulcooray/social_participation*. All the analyses were performed using *R version 4.1.2* for x86_64,linux-gnu. Reporting of this study follows the STROBE guidelines.

Results

Baseline characteristics of participants stratified by the outcome variable are presented in Table 1. In the 2016 follow-up, 12,079 (52.4%) reported a social participation frequency of less than at least once a week. Compared to the baseline, a total of 1817 (7.9%) participants reported a lower number of teeth category in 2013. Baseline characteristics associated with less frequent social participation in 2016 were older age, male sex, low income, low educational attainment, poor self-reported health, and lower frequency of social participation at baseline.

Table 2 provides risk ratios related to preventive and tooth loss scenarios after adjusting for the covariates, and the censoring during the follow-up. The results showed that the prevention of tooth loss had a positive effect on social participation. The largest improvement (8%) in social participation was observed with the scenario that retained ≥ 20 teeth among all older adults at each time point during the follow-up (scenario 4: RR= 1.08, 95%CI=1.05,1.11). Intervention that prevented individuals with 1-9 teeth becoming edentate (scenario 1) and the Intervention that prevented individuals tooth loss only in 1-9 teeth & 10-19 (scenario 2) did not significantly improve social participation. On the other hand, all emulated tooth loss scenarios (scenario 5 to 8) reduced the of social participation. The hypothetical scenario where all participants became edentate (Figure 2-S8) resulted in 11% reduction in the likelihood of frequent social participation among participants (RR= 0.89, 95%CI=0.84,0.94). The rest of the tooth loss scenarios resulted in 8% (scenario 7: RR= 0.92, 95%CI=0.88,0.95), 6% (RR= 0.94, 95%CI=0.91,0.97), and 4% (RR= 0.96, 95%CI=0.93,0.98), respectively in the descending order of severity of tooth loss. RR plot in Figure 3 indicates the presence of dose-response relationship between tooth loss and social participation among older adults.

Discussion

Our findings show that retaining more teeth during the follow-up period had a positive effect on social participation among older adults, whereas a decrease in the number of teeth during the follow-up had a negative effect on social participation among study participants. These findings support our hypothesis and are consistent with previous related research. Previous studies, however, used the number of teeth as the outcome variable (Aida et al. 2011; Takeuchi et al. 2013). Using longitudinal data and a robust causal inference method, this study added evidence related to the importance of maintaining an adequate number of teeth for frequent social participation among older adults. Given the consistent evidence that social participation improves older adults' health and well-being, mechanisms that lead to increased levels of social participation should be promoted and encouraged. In this context, our findings emphasise the importance of older adults retaining a greater number of teeth, not only for obvious benefits on oral functions such as mastication and speech, but also to have better social relationships and thus reap the benefits associated with social participation.

The mechanism that explains our findings is straightforward and intuitive. Teeth play an important role in social interactions such as smiling, speaking, eating, and maintaining facial aesthetics (Steele et al. 2004). As a result, tooth loss would naturally lead to a reluctance to engage in social activities. A recent cross-sectional study by Koyama et al. (2021) examined the association between the number of teeth and social isolation among older adults using data from Japan and England. They found that having fewer teeth was significantly associated with being socially isolated in both countries. Abbas et al. (2022) also found a similar association between teeth and dental prosthesis and being socially isolated in a longitudinal study. Although Koyama et al. and Abbas et al. investigated a different outcome, the mechanism between the number of teeth and social isolation may be similar to that of current study.

The analytical approach used in this study allowed us to obtain counterfactual estimates without needing to dichotomise the exposure variable (number of teeth). Thus, enabling the detection of gradual changes in social participation. Traditional methods contrast counterfactual outcomes only at the extremes of the exposure (i.e. "what if everyone is exposed vs. everyone is not exposed"). For example, with the same data, a traditional method would only allow us to estimate the difference between the counterfactual outcomes of being edentate versus having teeth, or having ≥ 20 teeth versus having < 20 teeth, which can be an unrealistic contrast (Rudolph et al. 2021). Furthermore, the LMPT approach minimised the positivity assumption violations (Petersen et al. 2010) (i.e., all had a non-zero probability of obtaining a given exposure level) as the counterfactual exposure levels (shifted levels) were assigned based on individual's observed number of teeth level at a particular time point (Appendix Figure 02). Also, by using TMLE to estimate corresponding statistical parameters, we were able to minimise parametric modeling assumptions regarding variables (Rose and Rizopoulos 2019; Díaz et al. 2021). Considering that the estimates in this study were contrasted against the natural outcome, we believe that our estimates are conservative. Therefore, estimated effect sizes were relatively small (e.g. retaining ≥ 20 teeth only improved the social participation by 8%). It might be unrealistic for a single exposure such as number of teeth alone to have a large effect on a complex behavioral outcome such as social participation. Thus, our estimates are grounded in the epidemiological reality, that outcomes related to well-being need multisectoral effort (Amri et al. 2022) and oral health may be a small yet important part of it. Though it is difficult to quantify how a given percentage increase in social participation translates into meaningful and desirable health or quality of life outcomes, any improvement in social participation due to retention of more teeth should be considered beneficial among the older population.

Even though we used hypothetical scenarios to estimate our research question, these scenarios are embedded in any real-world oral health promotion activities or interventions aimed at achieving at least minimal functional dentition in older adult populations. Realistically, to ensure at least a minimally functional dentition in old age, oral disease prevention should be an integral part of one's life course (Heilmann et al. 2015). Suboptimal emulated scenarios (e.g., preventing 10–19 teeth from becoming 1-9 teeth) in this study might be more in line with targeted interventions towards older adults, such as improving access to dental care by providing financial assistance (Cooray et al. 2020), orienting services to be aging-friendly, and collaborating with other geriatric health care providers to identify vulnerable groups for early interventions.

We note several limitations of our analysis and the data that may cause the estimates to be biased. First, the variables in this study were self-reported, which are prone to measurement and classification errors. Previous studies in Japan, however, have shown the validity of the self-reported number of teeth measure (Matsui et al. 2016). Second, causal inference with time-varying exposure necessitates no unmeasured confounding assumption at each time point (conditional exchangeability assumption) (Hernan 2006). Therefore, despite adjusting for multiple time-varying and time-invariant confounders, the possibility of unmeasured confounding cannot be ruled out. We reported E-values for estimates to reflect the potential effect of unmeasured confounding (VanderWeele and Ding 2017). Third, a large attrition of the sample population within six years (n= 52,053 at baseline to n= 24,872 at 2016 follow-up) was unavoidable as we used panel data with older adult participants who took part in all three waves of the JAGES. To minimise the bias due to this attrition, censoring status of all individuals were modeled into in our analysis, obtaining estimates accounted for censoring (Lendle et al. 2017). Additionally, we examined the baseline characteristics associated with censoring. Censoring was associated with a lower number of teeth at baseline. Having fewer teeth had a negative impact on social participation in our analyses. Fourth, in this study, only the organised social activities were captured. However, it might be useful to include informal social interactions as well. Fifth, the incidence of tooth loss in the observed data was only 7.6%; given the large number of covariates considered in this study, the possibility of positivity violation is higher when emulating counterfactual scenarios. Finally, we had no information about the locations of missing teeth in our data. Missing anterior teeth have a greater impact on facial aesthetics and speech, whereas missing posterior teeth would have a greater impact on masticatory functions. As a result, the location of missing teeth would have had a different effect on social participation.

Despite these limitations, our findings provide robust evidence that retaining more teeth positively associated with frequent social participation among Japanese older adults, whereas tooth loss negatively affects their social participation. This emphasises the importance of incorporating tooth loss prevention into interventions aimed at increasing social participation among older adults.

Conclusion

Hypothetical scenarios for tooth loss prevention improved social participation among Japanese older adults, whereas emulated tooth loss had negative effects. This suggests that retaining more natural teeth has a positive impact on social participation among older adults in Japan.

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All data used are from the JAGES survey. Data requests can be addressed to the JAGES data management committee via e-mail: dataadmin.ml@jages.net. All JAGES datasets have ethical or legal restrictions for public deposition due to inclusion of sensitive information from human participants. Software codes used in this study are publicly available at *https://github.com/upulcooray/social-participation.*

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Table 1: Baseline characteristics of participants stratified by the outcome.

Characteristics [a]	Frequent Social Participation	
	Yes *(N=8648)*	No *(N=16224)*
Age (years)	71.8 (4.5)	72.6 (5.2)
Sex:		
Male	3422 (30.7%)	7733 (69.3%)
Female	5226 (38.1%)	8491 (61.9%)
Household income (million Yen)	2.6 (1.6)	2.4 (1.6)
Educational attainment:		
12 years or more	1948 (41.0%)	2803 (59.0%)
10-12 years	3506 (38.3%)	5645 (61.7%)
6-9 years	3140 (29.3%)	7571 (70.7%)
6yrs	54 (20.8%)	205 (79.2%)
Social participation (2010):		
Yes	7340 (52.2%)	6721 (47.8%)
No	1308 (12.1%)	9503 (87.9%)
IADL score (2010)	12.3 (1.2)	11.7 (1.6)
Marital status:		
Married	6551 (34.8%)	12294 (65.2%)
Widowed,divorced, or unmarried	2097 (34.8%)	3930 (65.2%)
Self-rated health (2010):		
Very good	1527 (45.0%)	1865 (55.0%)
Good	6379 (35.0%)	11860 (65.0%)
Fair	694 (23.6%)	2243 (76.4%)
Poor	48 (15.8%)	256 (84.2%)
Eye impairment:		
Yes	1199 (31.5%)	2610 (68.5%)
No	7449 (35.4%)	13614 (64.6%)
Ear impairment:		
Yes	506 (29.2%)	1225 (70.8%)
No	8142 (35.2%)	14999 (64.8%)
Cancer:		
Yes	368 (31.1%)	815 (68.9%)
No	8280 (35.0%)	15409 (65.0%)
Heart disease:		
Yes	985 (30.5%)	2247 (69.5%)
No	7663 (35.4%)	13977 (64.6%)
Stroke:		
Yes	95 (29.9%)	223 (70.1%)
No	8553 (34.8%)	16001 (65.2%)
Number of household members		
1	1125 (38.8%)	1775 (61.2%)
2	4067 (36.1%)	7186 (63.9%)
3	1454 (32.9%)	2961 (67.1%)
4	577 (30.7%)	1300 (69.3%)
5	492 (31.8%)	1056 (68.2%)
6 or more	933 (32.4%)	1946 (67.6%)

[a] Mean (SD) for continuous variables; Frequency (%) for categorical variables

Table 2: Risk ratios (RR) and 95% confidence intervals (95% CI) calculated by contrasting emulated scenarios against the observed outcome estimate.

Contrast	RR [95% CI]	P value	E-value
Observed vs Scenario 1	1.01 [1.00-1.02]	0.173	1.09
Observed vs Scenario 2	1.01 [0.99-1.03]	0.392	1.09
Observed vs Scenario 3	1.06 [1.03-1.08]	<0.001	1.30
Observed vs Scenario 4	1.08 [1.05-1.11]	<0.001	1.36
Observed vs Scenario 5	0.96 [0.93-0.98]	0.001	1.26
Observed vs Scenario 6	0.94 [0.91-0.97]	<0.001	1.32
Observed vs Scenario 7	0.92 [0.88-0.95]	<0.001	1.40
Observed vs Scenario 8	0.89 [0.84-0.94]	<0.001	1.49

Scenario 1= What if edentate were 1-9;
Scenario 2= What if edentate were 1-9 & 1-9 were 10-19;
Scenario 3= What if edentate were 1-9 & 1-9 were 10-19 & 10-19 were >=20;
Scenario 4= What if everyone were >=20;
Scenario 5= What if >=20 were 10-19;
Scenario 6= What if >=20 were 10-19 & 10-19 were 1-9;
Scenario 7= What if >=20 were 10-19 & 10-19 were 1-9 & 1-9 were edentate;
Scenario 8= What if everyone were edentate

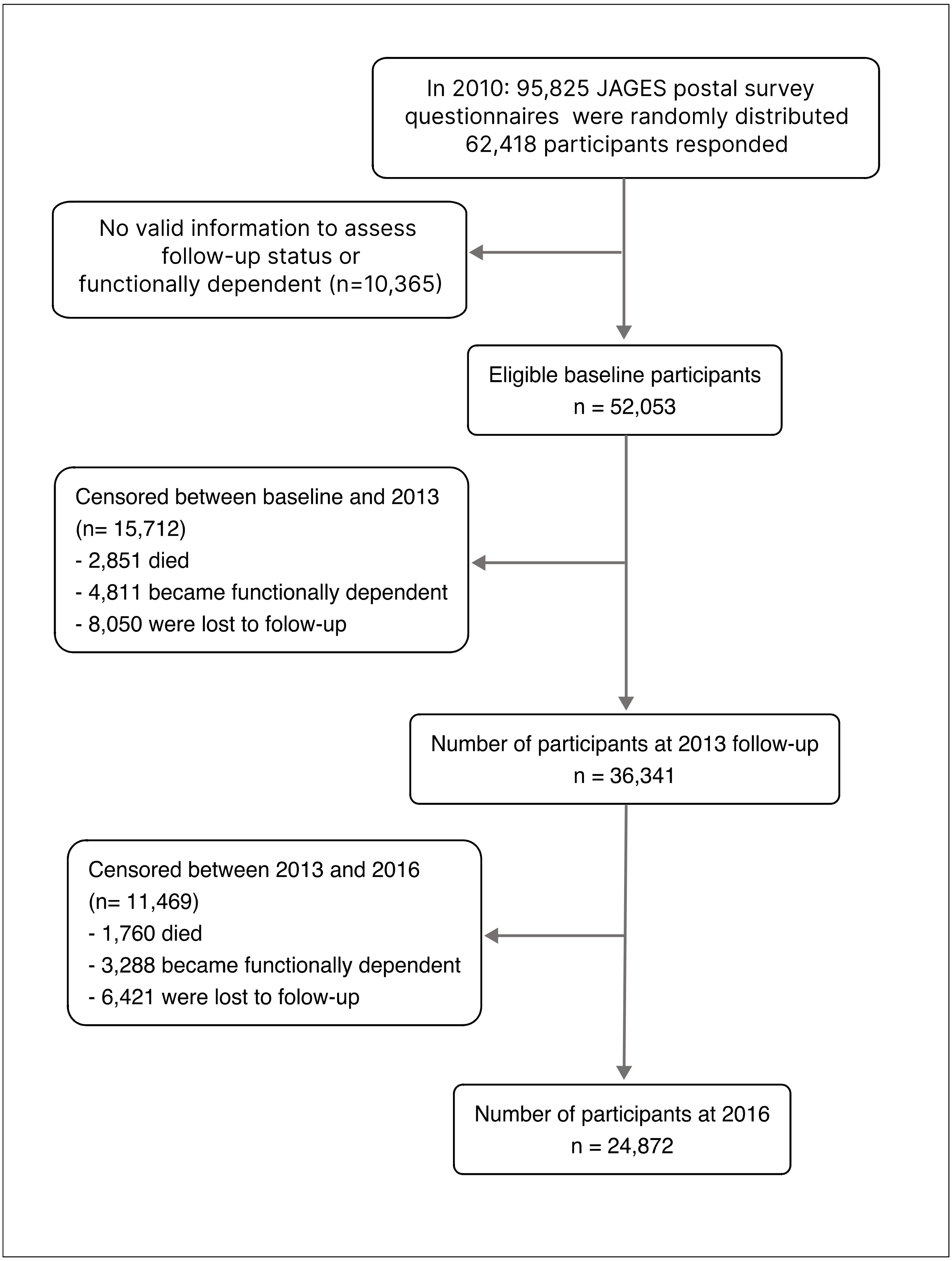

Figure 1: Study flow chart indicating the selection of analytical sample over the six-year follow-up period.

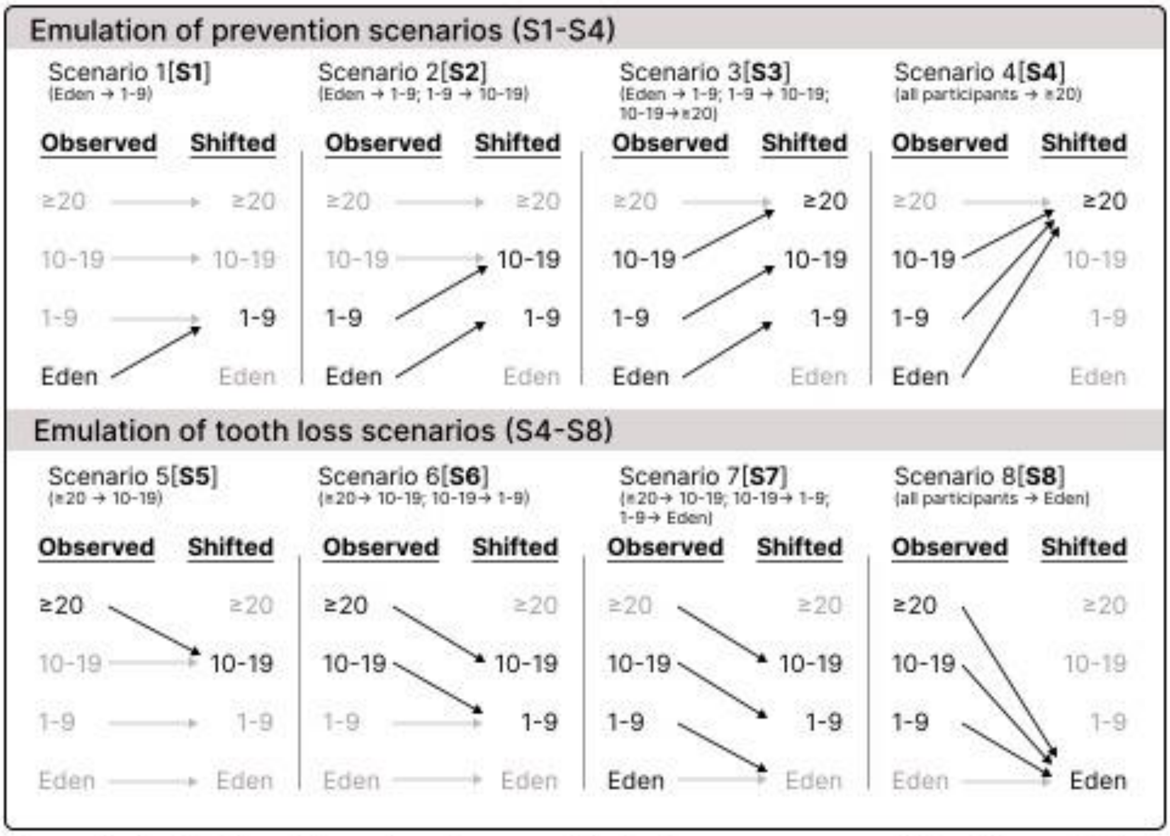

Figure 2: Illustration of how the observed level of exposure was shifted to emulate multiple exposure scenarios.

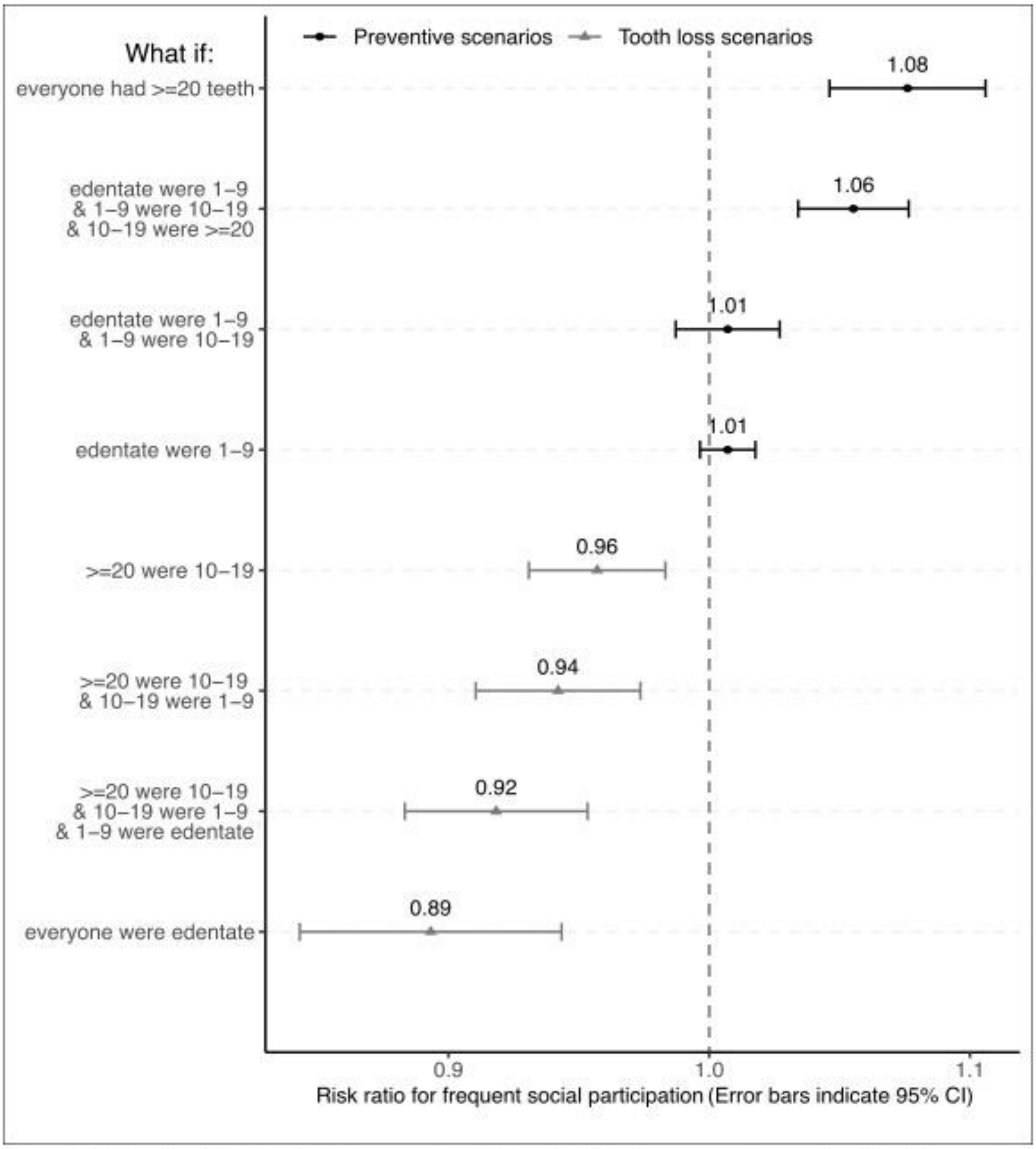

Figure 3: Risk ratios plot to indicate changes in social participation in response to number of teeth scenarios.

Appendix

Impact of teeth on social participation: Using modified treatment policies

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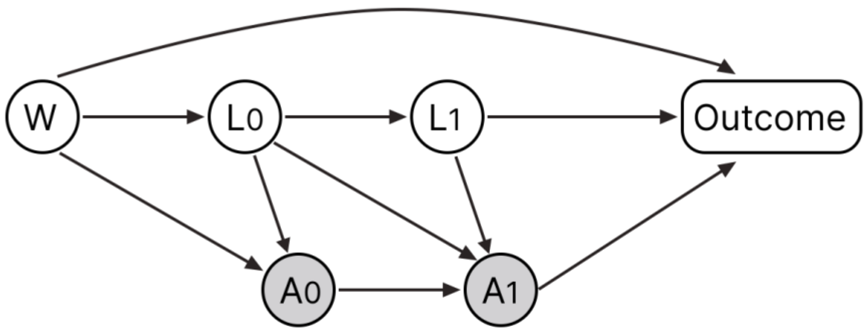
Appendix Figure 1: Hypothesized temporal associations between study variables



W= Age, Sex, Education, Baseline social participation
L = Income, Self-rated health, Marital status, IADL, Vision loss,
Hearing loss, Cancer, Heart disease, Stroke, Number of household members
(L0[measured at 2010]; L1[measured at 2013])
A0= Number of teeth 2010
A1= Number of teeth 2013
Outcome= Social participation at 2016

Appendix Figure 2: Illustrates the changes in longitudinal data when emulating exposure scenarios

Time-invariant covariates

Time-dependent covariates (Baseline)

Exposure value at baseline

Censoring indicator (after baseline)

Time-dependent covariates (2013)

Exposure value (2013)

Censoring indicator (after 2013)

OUTCOME (2016)

Observed Data

ID	W_1	...	W_n	$L0_1$	...	$L0_n$	A0	C1	$L1_1$	...	$L1_n$	A1	C2	Y
1	67	...	0	127	...	1	10-19	1	139	...	1	10-19	1	1
2	75	...	1	250	...	1	>20	1	216	...	0	>20	1	0
3	66	...	1	324	...	0	0	1	350	...	0	0	1	0
4	71	...	0	228	...	1	1-9	1	193	...	1	0	0	NA
5	65	...	1	219	...	0	10-19	1	316	...	1	1-9	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
N	79	...	0	169	...	0	0	0	NA	...	NA	NA	NA	NA

Example of emulating a prevention scenario (10-19 → >20 | 1-9 → 10-19 | 0 → 1-9)

Scenario 3 Data

ID	W_1	...	W_n	$L0_1$	...	$L0_n$	A0	C1	$L1_1$	...	$L1_n$	A1	C2	Y^
1	67	...	0	127	...	1	>20	1	139	...	1	>20	1	1
2	75	...	1	250	...	1	>20	1	216	...	0	>20	1	0
3	66	...	1	324	...	0	1-9	1	350	...	0	1-9	1	1
4	71	...	0	228	...	1	10-19	1	193	...	1	1-9	0	NA
5	65	...	1	219	...	0	>20	1	316	...	1	10-19	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
N	79	...	0	169	...	0	1-9	0	NA	...	NA	NA	NA	NA

Example of emulating a tooth loss scenario (>20→ 10-19| 10-19 → 1-9 | 1-9 → 0)

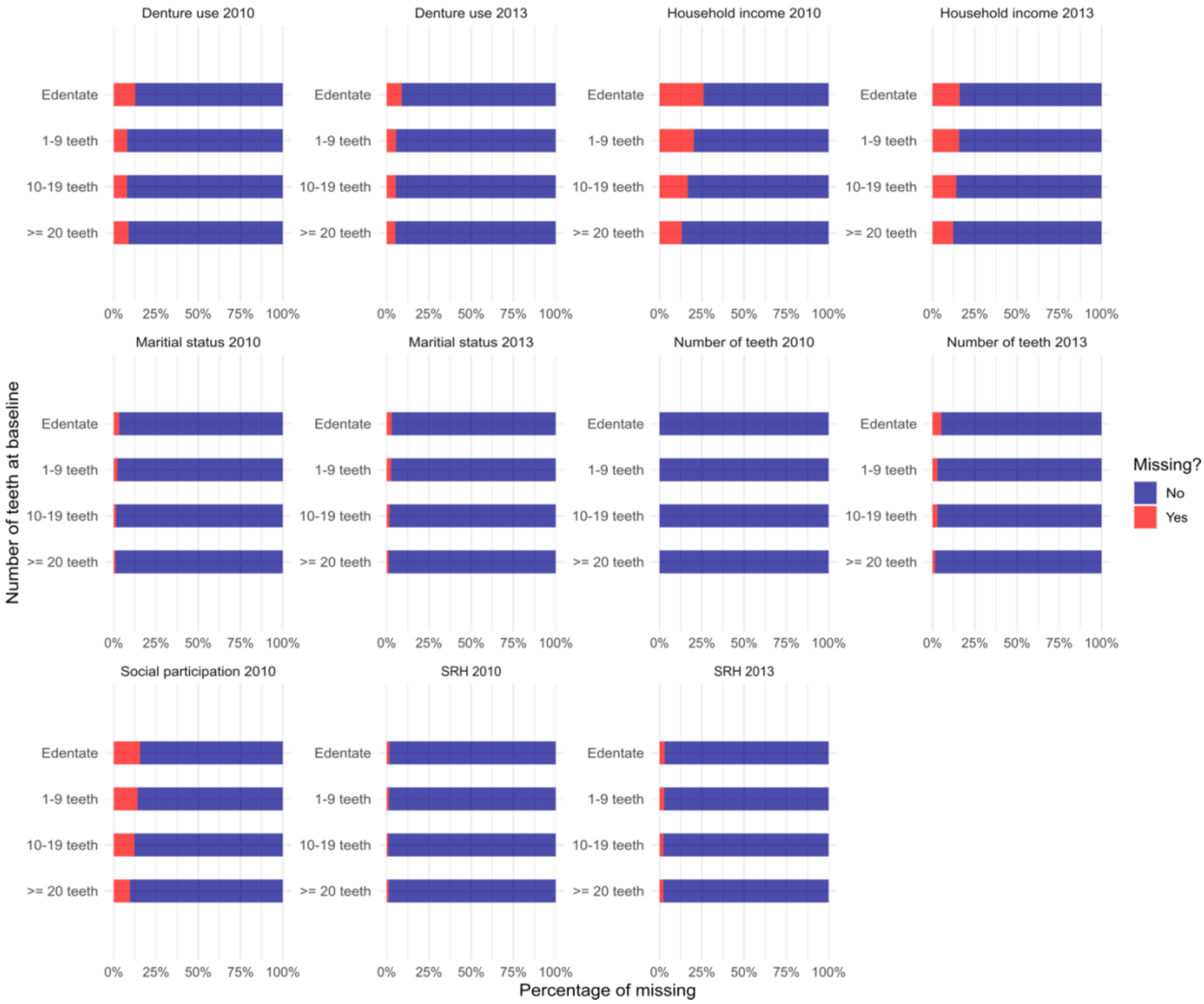
Scenario 7 Data

ID	W_1	...	W_n	$L0_1$	...	$L0_n$	A0	C1	$L1_1$	...	$L1_n$	A1	C2	Y^
1	67	...	0	127	...	1	1-9	1	139	...	1	1-9	1	1
2	75	...	1	250	...	1	10-19	1	216	...	0	10-19	1	0
3	66	...	1	324	...	0	0	1	350	...	0	0	1	0
4	71	...	0	228	...	1	0	1	193	...	1	0	0	NA
5	65	...	1	219	...	0	1-9	1	316	...	1	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
N	79	...	0	169	...	0	0	0	NA	...	NA	NA	NA	NA

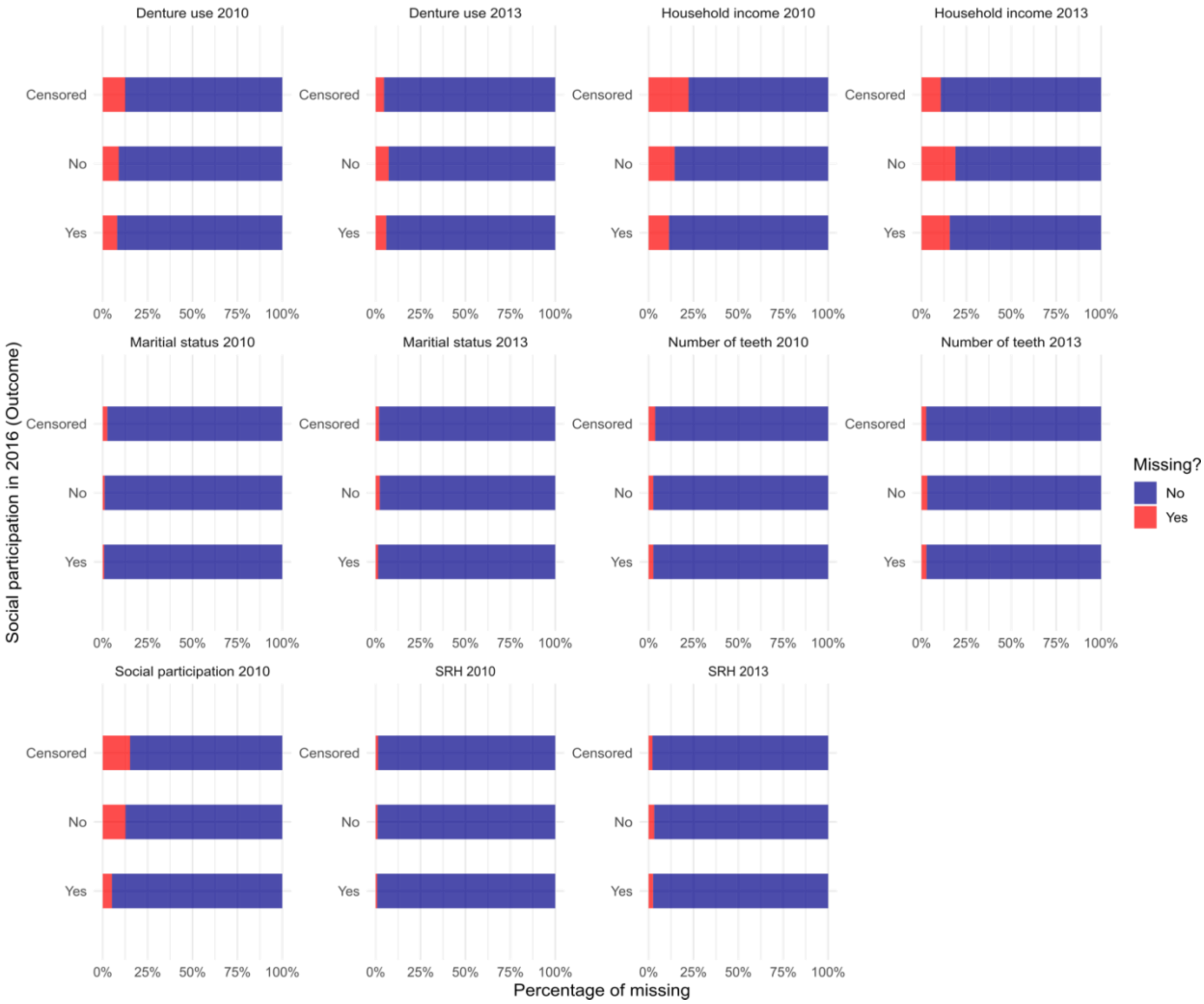
Y^ was Estimated using TMLE; **C1**=0 or **C2**=0 indicates loss to follow-up

NAs indicate data this is not available due to censoring

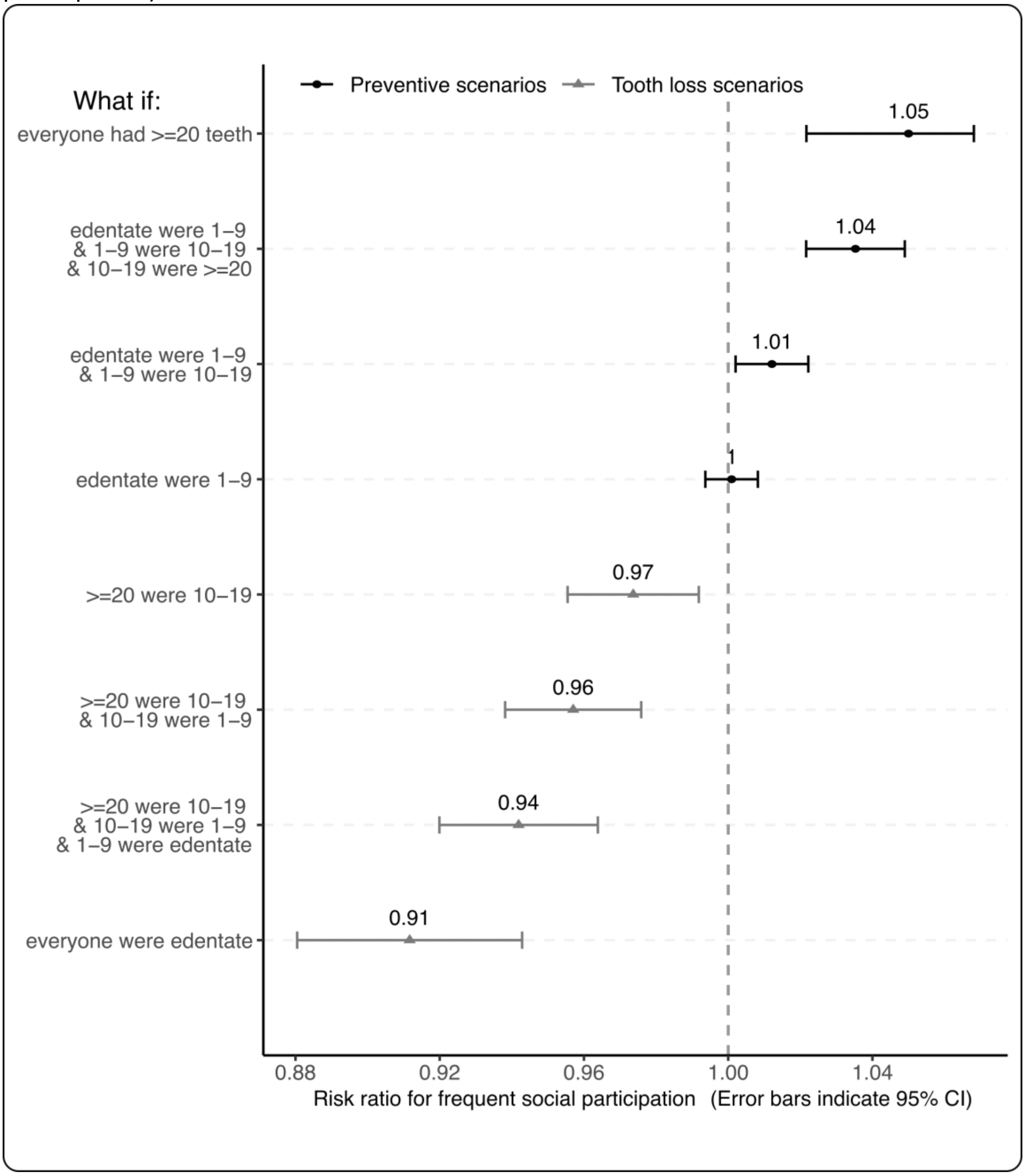
Appendix Figure 3: Percentage of missingness among key variables (stratified by exposure categories)



Appendix Figure 4: Percentage of missingness among key variables (stratified by outcome categories)



Appendix Figure 5: Risk ratios plot to indicate changes in social participation in response to number of teeth scenarios (at least "once a month" as the cut-off for frequent social participation)



Appendix Text box 01: Details of Super learner algorithm usage

Super Learner Algorithm

The super learner algorithm is a machine learning method that combines multiple models, also known as base learners (in this study we used *glm, gam*, and *xgboost*), to improve the overall performance of the final model. The idea behind it is that by combining the predictions of multiple models, the final model will have a lower error rate than any of the individual base models (Laan 2007). The super learner algorithm can be used with a variety of different types of base learners, such as decision trees, regressions, and neural networks. Simply put, the super learner algorithm is a way to improve the accuracy of a prediction (used in propensity score calculation and g-computation) by combining multiple models. Previous studies have suggested that having a mix of parametric and non-parametric base models improves the accuracy of prediction with epidemiological data (Gao et al. 2018). The rationale behind *glm, gam, xgboost* is that *glm* can capture linear relationships, gam to capture non-linear relationships, and *xgboost* to capture more complex relationships.

In this study we used default settings used in the Super Learner R package for *glm, gam, xgboost* base models.

Eg:

SL.xgboost(ntrees=1000,max_depth=4,shrinkage=0.1,minobspernode=10, nthread=1)

SL.gam(deg.gam=2 <- *number of knots*
cts.num=4 <- *variable with more than 4 unique values to be continuous and able to be in smoothing splines.)*

References:

van der Laan MJ, Polley EC, Hubbard AE. Super learner. Stat Appl Genet Mol Biol. 2007;6:Article25. doi: 10.2202/1544-6115.1309. Epub 2007 Sep 16. PMID: 17910531.

Gao, C., Sun, H., Wang, T. et al. Model-based and Model-free Machine Learning Techniques for Diagnostic Prediction and Classification of Clinical Outcomes in Parkinson's Disease. Sci Rep 8, 7129 (2018). https://doi.org/10.1038/s41598-018-24783-4

Appendix Table 1: Risk ratios (RR) and 95% confidence intervals (95% CI) when at least once a month social participation was used as the cut-off

Contrast	RR [95% CI]	P value	E-value
Observed vs Scenario 1	1.00 [0.99-1.01]	0.697	1.03
Observed vs Scenario 2	1.01 [1.00-1.02]	0.018	1.12
Observed vs Scenario 3	1.04 [1.02-1.05]	<0.001	1.23
Observed vs Scenario 4	1.05 [1.02-1.07]	<0.001	1.26
Observed vs Scenario 5	0.97 [0.96-0.99]	0.003	1.19
Observed vs Scenario 6	0.96 [0.94-0.98]	<0.001	1.26
Observed vs Scenario 7	0.94 [0.92-0.96]	<0.001	1.32
Observed vs Scenario 8	0.91 [0.88-0.94]	<0.001	1.42

Scenario 1= What if edentate were 1-9;
Scenario 2= What if edentate were 1-9 & 1-9 were 10-19;
Scenario 3= What if edentate were 1-9 & 1-9 were 10-19 & 10-19 were >=20;
Scenario 4= What if everyone were >=20;
Scenario 5= What if >=20 were 10-19;
Scenario 6= What if >=20 were 10-19 & 10-19 were 1-9;
Scenario 7= What if >=20 were 10-19 & 10-19 were 1-9 & 1-9 were edentate;
Scenario 8= What if everyone were edentate

Appendix Table 2: Baseline characteristics of participants by follow-up status

Characteristic	Follow-up status: Remained N=24872	Became ineligible N=8099	Died N=4611	Lost to follow-up N=14471
Mean Age (±SD)	72.3 (5.0)	78.9 (6.2)	77.7 (6.7)	73.0 (5.4)
Sex:				
Male	11155 (46.2%)	3086 (12.8%)	3033 (12.5%)	6897 (28.5%)
Female	13717 (49.2%)	5013 (18.0%)	1578 (5.7%)	7574 (27.2%)
Household income	2.5 (1.6)	2.2 (1.5)	2.2 (1.6)	2.3 (1.7)
Educational attainment:				
12yrs	4699 (53.4%)	1076 (12.2%)	657 (7.5%)	2366 (26.9%)
10_12yrs	9039 (53.3%)	2281 (13.5%)	1285 (7.6%)	4348 (25.6%)
6_9yrs	10546 (44.3%)	3940 (16.5%)	2306 (9.7%)	7032 (29.5%)
6yrs	251 (21.4%)	437 (37.3%)	197 (16.8%)	286 (24.4%)
Baseline social participation:				
Yes	12809 (55.0%)	2943 (12.6%)	1552 (6.7%)	5987 (25.7%)
No	9608 (43.3%)	3780 (17.0%)	2351 (10.6%)	6433 (29.0%)
IADL score (2010)	11.9 (1.5)	10.7 (2.6)	10.8 (2.6)	11.6 (1.8)
Marital status:				
Married	18673 (51.0%)	4505 (12.3%)	3102 (8.5%)	10335 (28.2%)
Widowed,divorced, or unmarried	5947 (41.0%)	3364 (23.2%)	1380 (9.5%)	3806 (26.3%)
Self-rated health (2010):				
Very good	3364 (55.8%)	529 (8.8%)	349 (5.8%)	1790 (29.7%)
Good	18082 (50.7%)	4823 (13.5%)	2697 (7.6%)	10053 (28.2%)
Fair	2900 (34.1%)	2227 (26.2%)	1177 (13.8%)	2207 (25.9%)
Poor	296 (23.5%)	379 (30.1%)	328 (26.1%)	256 (20.3%)
Eye impairment:				
Yes	2968 (41.5%)	1644 (23.0%)	685 (9.6%)	1849 (25.9%)
No	15589 (47.7%)	5250 (16.1%)	3102 (9.5%)	8722 (26.7%)
Ear impairment:				
Yes	1374 (36.0%)	1060 (27.7%)	489 (12.8%)	897 (23.5%)
No	17183 (47.7%)	5834 (16.2%)	3298 (9.2%)	9674 (26.9%)
Cancer:				
Yes	873 (38.7%)	348 (15.4%)	566 (25.1%)	470 (20.8%)
No	17684 (47.1%)	6546 (17.4%)	3221 (8.6%)	10101 (26.9%)
Heart disease:				
Yes	2501 (40.8%)	1327 (21.6%)	813 (13.2%)	1496 (24.4%)
No	16056 (47.7%)	5567 (16.5%)	2974 (8.8%)	9075 (27.0%)
Stroke:				
Yes	235 (36.7%)	153 (23.9%)	92 (14.4%)	161 (25.1%)
No	18322 (46.8%)	6741 (17.2%)	3695 (9.4%)	10410 (26.6%)

Family members				
1	2681 (44.8%)	1206 (20.2%)	511 (8.5%)	1581 (26.4%)
2	10737 (51.8%)	2792 (13.5%)	1627 (7.9%)	5564 (26.9%)
3	4180 (49.2%)	1140 (13.4%)	702 (8.3%)	2476 (29.1%)
4	1752 (44.5%)	695 (17.6%)	358 (9.1%)	1133 (28.8%)
5	1453 (45.6%)	535 (16.8%)	358 (11.2%)	841 (26.4%)
6 or more	2701 (47.5%)	772 (13.6%)	607 (10.7%)	1612 (28.3%)

Appendix Table 3: Results of logistic regression predicting frequent social participation among older adults after six-years.

Term	Estimate (OR)	Lower CI	Higher CI	p value
Edentate	Ref	Ref	Ref	-
1-9 teeth	1.15	1.02	1.29	0.025
10-19 teeth	1.24	1.10	1.39	<0.001
20 or more teeth	1.43	1.27	1.60	<0.001

Estimate were adjusted for age, sex, years of formal education, social participation, equalized annual household income, self-rated health, Instrumental Activities of Daily Living (IADL) score, vision loss, hearing loss, cancer, heart disease, stroke, number of household members, and marital status at baseline.