Effect of number of teeth on social participation among older adults in Japan: using modified treatment policy approach

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Abstract word count: 252

Total word count: 3063

Number of tables: 2

Number of figures: 3

Number of reference: 34

Keywords: Casual inference, Modified treatment policy, Targeted minimum loss-based estimation, Social participation, Older adults

## Abstract (word limit 250)

### Background

Participating in social activities and interacting with others in the community has numerous positive effects on older adults’ health and quality of life. We aimed to estimate the causal effect of number of teeth on social participation among older adults in Japan.

### Methods

Longitudinal data (baseline=2010, follow-ups=2013 and 2016) from 24,872 participants of the Japan Gerontological Evaluation Study was used in the analysis. We employed a longitudinal modified treatment policy approach to determine the effect of several hypothetical scenarios (tooth loss prevention and tooth loss) on social participation after 6 year follow-up. Corresponding statistical parameters were estimated using targeted minimum loss-based estimation (TMLE) method. Number of teeth category (edentate, 1-9 teeth, 10-19 teeth, 20 teeth) was treated as time-varying exposure, and the outcome estimates were adjusted for time-varying (income, self-rated health, marital status) and time-invariant (age, sex, education, baseline social participation) covariates.

### Results

Social participation consistently improved when counterfactual tooth loss prevention scenarios were implemented. The most intensive prevention scenario (maintaining 20 among each participant) improved the social participation by 9% (OR= 1.09, 95%CI=1.04,1.14). Contrary, counterfactual tooth loss scenarios gradually decreased the social participation resulting 15% (OR= 0.85, 95%CI=0.80,0.90) reduction in social participation if the participants were edentate throughout the follow-up.

### Conclusions

This study provides causal evidence that having a higher number of teeth and maintaining a functional dentition positively affects social participation among Japanese older adults, while being edentate or having relatively fewer teeth negatively affects 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 general1. Social participation among older adults is an essential component of healthy ageing because it has numerous positive effects on both individuals and society2. Previous studies have linked higher levels of social participation to higher life expectancy, better health-related quality of life, well-being, and functioning of older adults3–5. Community-level health promotion and prevention activities such as physical activity, smoking and alcohol interventions, could also be facilitated through social engagement6. On the other hand, a wide range of determinants, including health-related factors, influence older adults’ level of social participation7,8.

Teeth and oral health 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 diseases9. Previous studies have consistently linked social and neighbourhood related factors such as social capital and social participation to oral health related outcomes among older adults10–12. much less is known about the effect of oral health on participation in social activities. Experimental studies to evaluate the potential causal effect of the remaining number of teeth on social participation are not practically feasible, further complicated by the time varying nature of the exposure (number of teeth) and confounders. Longitudinal modified treatment policy (LMTP) approach can be adapted to overcome some of these limitations for causal inference with observational data13.

LMTP is a recently developed non-parametric alternative that can be used to define causal effects14. The literature for causal inference based on binary exposures is extensive15. However, dichotomisation of the exposure using a 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 level14. In other words, this framework can be adapted to quantify counterfactual outcomes for questions such as, “What would have happened to the prevalence of social participation if everyone in the study population increased or decreased their number of teeth by a certain amount?”, or “What if everyone in the study population retained a >=20 teeth?”. Furthermore, the corresponding statistical parameters for LMTP can be estimated using sophisticated doubly-robust statistical estimators, such as the targeted minimum loss-based estimation (TMLE), which allows for the use of flexible machine learning predictions to obtain marginal effects avoiding parametric modelling assumptions16,17.

This study estimates the effect of the number of remaining teeth on social participation among older adults while taking the time-varying nature of variables into account. LMTP was used to dynamically shift the observed level of exposure (number of remaining natural teeth) to new levels in order to investigate its effect on social participation among functionally independent older adults in Japan over a 6-year period. We hypothesised that as the prevention of tooth loss improves the social participation and the social particiation declines due to tooth loss among older adults.

## Methods

### Data

Data from the Japan Gerontological Evaluation Study (JAGES) was used in this study18. JAGES is an on-going nationwide cohort study for functionally independent older adults in Japan aged 65 years or over. For this analysis, data from the 2010 survey as the baseline and two subsequent follow-up surveys (2013 and 2016) were used. From a total of 52,053 functionally independent participants in the baseline survey, 24,872 individuals responded to all three waves (i.e., 2010, 2013, and 2016). During the 6 years of follow-up 4611 died, 8099 became ineligible as they became functionally dependent, and 14,471 were lost to follow-up due to other reasons (study flow chart in Figure 1). A comparison of baseline characteristics by participants’ follow-up status (i.e., died/ became ineligible/ lost to follow-up/ or remained) is reported in Supplementary Table S1.

### Outcome variable

Social participation in 2016 was the outcome in this study. 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 month or more frequently (vs. less frequently or never) was defined as indicative of social participation (1=participation, 0=non-participation)19.

### Exposure

The number of remaining natural teeth at the time of the surveys in 2010 and 2013 was used as a time-varying exposure in the analysis. The self-reported number of teeth was recorded using the response to the question, “How many natural teeth do you currently have?” (Instructions: capped/crowned teeth should be counted as “natural teeth”). The responses of participants were recorded in four categories (i.e., 20 teeth/ 10-19 teeth/ 1-9 teeth/ no teeth).

### 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. As time-invariant covariates, age (range 65–99 years), sex (male/female), years of formal education (6 years, 6-9 years, 10-12 years, 12 years or more), and social participation in 2010 (outcome at the baseline) were adjusted for. Equalised annual household income (million yen), self-rated health (very good/ good/ fair/ poor), and marital status (married/ single, widowed or divorced) were used as time-varying covariates (measured in 2010 and 2013).

### Statistical analysis

The hypothesised temporal associations between study variables are shown in the directed acyclic graph (DAG- supplementary?). A descriptive analysis was performed to identify the characteristics of participants stratified by the outcome (social participation in 2016). Then, to specify the impact of number of teeth on social participation, the observed level of number of teeth of each individual at each time point was shifted to new levels to mimic four tooth loss prevention scenarios and four tooth loss scenarios. Specifically, following hypothetical scenarios were estimated to detect any dose-response effect associated with remaining natural teeth and the social participation.

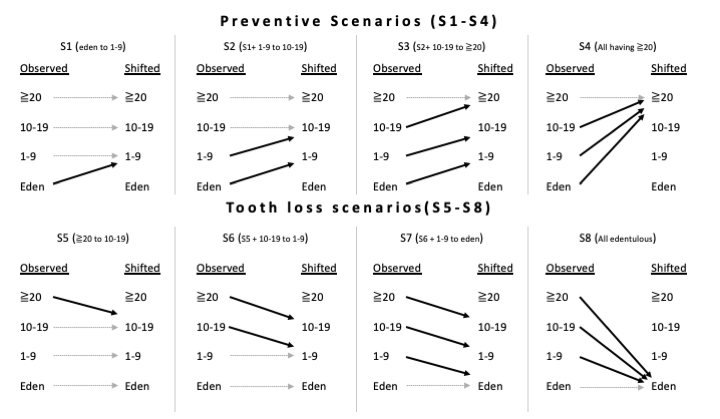
Tooth loss prevention scenarios; (Scenario 1 to 4, see the Figure 2)

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; (Scenario 5 to 8, see the Figure 2)

1. “What if participants with 20 teeth became 10-19 teeth”
2. “What if participants with 20 teeth became 10-19 teeth and participants with 10-19 teeth became 1-9 teeth”
3. “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”
4. “What if all participants became edentate”

Figure 2 illustrates how the observed level of exposure was shifted to elicit above hypothetical exposure scenarios.



To estimate the level of social participation with the shifted (and the observed) exposure, we used TMLE14,17. In TMLE, the probability of the exposure conditional on covariates (propensity score model), and the conditional probability of the outcome given exposure and covariates (g-computation model) were estimated to obtain unbiased estimation of the counterfactual outcomes17,20. If either the exposure model or the outcome model was consistently estimated, unbiased estimates could be obtained (hence doubly-robust)21. To increase the likelihood of robust specification of exposure and outcome models, Super Learner, an ensemble method that uses weighted combinations of multiple machine learning algorithms was used22–24. Generalised linear models (*glm*), generalised additive models (*gam*), and extreme gradient boosting models (xgboost) were used within the Super Learner25. Finally, the TMLE estimates of each hypothetical scenario was contrasted against the outcome estimate under observed exposure to calculate causal odds ratios (OR) and 95% confidence intervals (95% CI) for each respective scenario. All estimates were appropriately controlled for above mentioned time-variant, time-invariant covariates and attrition of the study population due to censoring. Furthermore, E values were calculated to report the potential impact of unmeasured confounders26.

For the imputation of missing data random forest based multivariate imputation by chained equations (MICE) was used. In imputing complex epidemiologic data, random forest MICE has been shown to produce less biased parameter estimates and better confidence interval convergence compared to parametric MICE27. Analyses were performed using five imputed datasets and the estimates were pooled using Rubin’s rules28. MICE was implemented using mice R package29. The distribution of missingness among covariates in relation to outcome and exposure are shown in Supplementary Figure S1 and S2. The lmtp R package was used to compute TMLE estimates with Super Learner for each scenario30. Main R codes used to generate our results are provided in Supplementary material. All the other supplimentary codes that used in analyses can be found at https://github.com/upulcooray/social-participation. All the analyses were conducted in using R version 4.1.2 for x86\_64, linux-gnu.

## Results

Baseline characteristics of participants stratified by the outcome variable are presented in Table 1. In the 2016 follow-up, 12,079 (52.4%) people reported a social participation frequency of less than at least once a month. 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 baseline social participation.

Table 2 provides the causal odds ratios related to four preventive scenarios and four tooth loss scenarios after adjusting for time-invariant (age, sex, education, baseline social participation) and time-varying (income, self-rated health, marital status) covariates and the censoring of participants during the six year follow-up. The results showed that the prevention of tooth loss had a positive effect on social participation. When the intensity of preventive interventions were increased (scenario 1 to 4) social participation increased in response. The largest improvement (9%) in social participation was observed with the hypothetical intervention that retained 20 teeth among all older adults at each time point during the six year follow-up (scenario 4: OR= 1.09, 95%CI=1.04,1.14). The intervention that prevented individuals with 1-9 teeth becoming edentate did not significantly improve the social participation in study population (scenario 1: OR= 1.01, 95%CI=1.00,1.02). On the other hand, tooth loss scenarios (scenario 5 to 8) significantly reduced the prevalence of social participation. The hypothetical scenario where all participants became edentate (see S8 in Figure 2) resulted in 15% reduction in the likelihood of social participation among study participants (OR= 0.85, 95%CI=0.80,0.90). Rest of the tooth loss scenarios resulted in 11% (scenario 7: OR= 0.89, 95%CI=0.84,0.93), 7% (OR= 0.93, 95%CI=0.89,0.96), and 4% (OR= 0.96, 95%CI=0.92,0.99), respectively in the descending order of severity of tooth loss. Supplementary Table xx reports TMLE outcome estimates for each scenario and the observed data which were used to compute above reported ORs.

Odds ratio plot in Figure 3 shows how the odds for social participation changed with each number of teeth scenario. It indicates the presence of clear dose-response relationship between number of teeth and the social participation among older adults.

## Discussion

To estimate the impact of the number of remaining teeth on social participation among older adults in Japan, we used an analytic approach that allows us to estimate the effects of different levels of exposure over time while controlling for time-variant covariates. The estimates were obtained using a doubly-robust estimator (TMLE) in combination with a machine learning-based ensemble (Super Learner). To the best of our knowledge, this is the first study to estimate the effect of number of remaining natural teeth on social participation.

Our findings show that retaining more natural teeth (preventing tooth loss) during the follow-up period had a positive effect on social participation among older adults. Whereas, decrease in the observed number of teeth (tooth loss) during the follow-up had a negative effect on social participation among study participants. These findings support our hypothesis and consistent with previous related research. Previous studies, however, were based on cross-sectional data and used the number of teeth as the outcome variable10,12. 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 leads 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 aesthetics31. 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.32 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. Although Koyama et al. investigated a different outcome (i.e., social isolation), the mechanism between the number of teeth and social isolation may be similar to that of current study.

We employed a powerful yet underutilised LMTP approach to define causal effects without needing to dichotomise the number of teeth variable. The LMPT approach naturally satisfied the positivity assumption33 (i.e., all people had a non-zero probability of obtaining a specific exposure level) in defining causal effects as the conterfactual exposure levels (shifted exposure levels) were assigned based on the each individual’s observed number of teeth level at each time point. Furthermore, by using doubly robust TMLE to estimate the corresponding statistical parameters, we were able to minimise parametric modeling assumptions14. Traditionally, causal estimates could only be obtained by contrasting conterfactual outcomes at the exposure’s extremes (i.e. “what if everyone exposed vs everyone not exposed” - due to forced binary exposures). In this study, for example, a traditional method would have only allowed us to estimate the difference between the counterfactual outcomes of being edentate versus having teeth, or having 20 or more teeth versus having less than 20 teeth. However, using LMTP and TMLE combination, we were able to estimate counterfactual outcomes across multiple different levels of the exposure. Hence, enabling us to detect a gradual increase in social participation at with tooth loss prevention scenarios and opposite effect with tooth loss scenarios (Figure 3). Furthermore, estimates reported in this study are fairly conservative compared to causal estimates reported using traditional causal inference methods.

TMLE estimate under the observed level of number of teeth could be contrasted against counterfactual outcomes under hypothetical exposure levels to estimate the expected change in mean population outcome (Figure 3-b).

Our analysis has several limitations, some of which may cause 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 showed the validity of the self-reported number of teeth measure34,35. Second, causal inference for time-varying exposure necessitates no unmeasured confounding assumption at each time point (conditional exchangeability assumption)36. Therefore, despite adjusting for multiple time-varying and time-invariant confounders, as well as baseline levels of social participation, the possibility of unmeasured confounding cannot be ruled out (E-values for all point estimates are reported in Table 2 to reflect the potential effect of unmeasured confounding)26. Third, we used panel data with older adult participants who took part in all three waves of the JAGES. Therefore, we had a large attrition of our sample population within six years(n= 52 053 at baseline to n= 24,872 at 2016 follow-up). To minimise the bias due to this attrition, we included censored participants’ information in our analysis to obtain estimates controlled for censoring. Additionally, we examined the baseline characteristics associated with censoring (supplementary table 1), and found that it was associated with a lower number of teeth at baseline. According to the study results, having fewer teeth had a negative impact on social participation. As a result, any selection bias caused by attrition would have resulted in an underestimation of the effect of number of teeth on social participation.

Future research is needed to look into some of the missing elements in our study. We were unable to assess the quality of social interactions in this study, which is just as important in obtaining the health benefits associated with social participation. Furthermore, we were unable to locate the locations of missing teeth in our data. Missing anterior teeth would have had a greater impact on facial aesthetics and speech, whereas missing posterior teeth (molars and premolars) would have had a greater impact on masticatory functions. As a result, the location of missing teeth would have had a different impact on social participation.

Despite these limitations, our findings provides robust evidence that having a higher number of teeth positively affects social participation among Japanese older adults, while being edentate or having a relatively lower number of teeth negatively affects their social participation. This emphasises the importance of incorporating tooth loss prevention into interventions aimed at increasing social participation among older adults. Our findings also indicated that increasing the number of teeth improved social participation, which is comparable to the potential impact of effective dental prosthetic treatments to restore missing teeth.

## Conclusions

Having a higher number of teeth positively affects social participation among Japanese older adults, while being edentate or having a relatively lower number of teeth negatively affects their social participation.

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