***Supplementary data (online only)***

**Title**

Heat-not-burn tobacco product use in Japan: its prevalence, predictors, and perceived symptoms from exposure to secondhand heat-not-burn-tobacco aerosol

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**Supplementary methods**

***Variables***

*Combustible tobacco use status*

Baseline smoking status was categorized as “never-smoker,” “former smoker,” or “current smoker.” Panelists were asked: “Please choose your current status regarding paper-wrapped and roll-your-own cigarettes separately,” and the response options were “never-user,” “former non-regular user,” “former regular user,” and “current user.” Respondents who currently smoked combustible tobacco (paper-wrapped and/or roll-your-own cigarettes) were considered current smokers. Those who reported former use and did not currently smoke either type of cigarette were considered former smokers. Those who had never-smoked were considered never-smokers.

Intention to quit was measured, among current smokers, with the question “Are you planning to quit smoking: within the next month? Within the next 6 months? Sometime in the future, beyond 6 months? Or not planning to quit?” The latter two responses were combined as “having no intention to quit within 6 months.” Therefore, current smokers were further categorized as “current smokers with intention to quit within 6 months” or “current smokers with no intention to quit within 6 months.”

*HNB-tobacco/e-cigarette use status*

Baseline HNB-tobacco/e-cigarette use status was used as a baseline characteristics variable, categorized into “never-user” and “ever-user.” In the 2015 baseline survey, panelists were asked about their use of each of the following products: nicotine e-cigarettes, non-nicotine e-cigarettes, e-cigarettes with unknown nicotine content, Ploom, and IQOS; the question asked was “Please choose your current status for each product,” and the response options were “never-user,” “former non-regular user,” “former regular user” and “current user.” The latter three responses were combined and defined as “ever-user.” Respondents who reported ever use of at least one type of new tobacco products were considered baseline ever-users of electronic tobacco products (HNB-tobacco/e-cigarette). Since we knew that the percentage of HNB-tobacco/e-cigarette current use in 2015 was very low in the baseline survey, a separate category of current-user was not used; that is, baseline status of never-user or ever-user (former and current users) was used in the analyses.

HNB products add to an existing array of electronic nicotine delivery products that may leave consumers confused. While all are clearly different from combustibles, many consumers cannot differentiate e-cigarettes from other electronic tobacco products, such as IQOS, especially in Japan,1 where people largely perceive these products as belonging to the same group of “electronic tobacco products” (personal communications, recent newspaper articles, web blogs, Twitter, and Facebook).

Finally, HNB-tobacco/e-cigarette never-users who answered “yes” to the question “Do you want to try HNB-tobacco/e-cigarette in future?” were defined as “HNB-tobacco/e-cigarette never-user with preference for HNB-tobacco/e-cigarette use.”

***Other factors***

Baseline status in terms of sex (men or women), age (15-19 years, 20-29, 30-39, 40-49, 50-59, and 60-69), workplace indoor smoke-free status (no ban, complete ban, or not working/do not know), equivalent household income (quartile), housing tenure (home-owner or not), education (junior high school/high school, or university /technical school/college or more), marital status (married, never married or divorced /widowed), alcohol consumption (never, former or current drinker), self-rated health (excellent/very good/good or fair/poor), and area-level deprivation index of living place (quartile) were used as baseline characteristics.

*Workplace indoor smoking ban status*

Workplace status was measured using the question: “Which of the following is closest to the smoking situation of your indoor workplace (in the case of students, school)?” Options included: You can smoke anywhere; There is a smoking room/smoking area; All smoke-free; Not applicable (not working, etc.); and Do not know. The response of “all smoke-free” was defined as indicating a “complete indoor ban.”

*Area-level Deprivation Index (ADI)*

We used the area-level deprivation index (ADI), a composite indicator of census variables, to capture the geographical accumulation of deprived population living in a given postal district. This ADI was proposed as a Japanese variant of Gordon’s deprivation index,2 which was originally designed for the UK context (initially for estimating the rate of households in poverty in a ward in the UK and subsequently used at a finer geographical scale to assess changes in poverty concentrations.3 4 The details of how this index was constructed and its association with health disparities in Japan were given in a previous study.5 The derived ADI is calculated as:

ADI = *k* (2.99 \* proportion of elderly-couple households + 7.57 \* proportion of elderly-single households + 17.4 \* proportion of single-mother households + 2.22 \* proportion of rented homes + 4.03 \* proportion of sales and service workers + 6.05 \* proportion of agricultural workers + 5.38 \* proportion of blue-collar industrial workers + 18.3 \* unemployment rate),

where *k* is a balancing factor, which should be a positive constant so that ADI is positively associated with the rate of households living in poverty in a given postal district. In this study, ADI was first computed for Cho-Aza, a small-area census unit, as of 2005, and then its average value was calculated for each postal district using a geographic information system. As the result, we obtained ADI values for all of 113,291 postal districts (average number of households per district is 299.5) across the country. We divided the aggregated postal districts into quartiles based on ADI; higher quartiles represent more disadvantaged neighborhoods.

***Analysis to adjust for “being an internet survey respondent”***

Although internet surveys have several advantages compared to traditional surveys, a major potential drawback is that they may not be representative of the general population, because people who access the internet may have distinctive characteristics. Previous studies have suggested that adjusted estimates using inverse probability weighting (IPW) obtained from a propensity score (calculated by logistic regression models using basic demographic and socioeconomic factors such as education) from an internet-based convenience sample provide similar estimates of parameters, or at least reduce the differences compared to probability-sample-based estimates.1 6 7 We used a probability sample representative of the Japanese population according to the Comprehensive Survey of Living Conditions of People on Health and Welfare (CSLCPHW).8 Data from two surveys (internet survey and CSLCPHW) were pooled and used for a logistic regression model with covariates to estimate the probability of “being a respondent in an internet survey,” that is, the propensity score. Detailed methods are available in our previous report.1

*Variables used in the adjustment*

Variables available in both surveys (internet survey and CSLCPHW) were used for the adjustment; they were area of residence, as defined by the National Population Mobility Survey conducted by the Japanese Ministry of Health, Labour and Welfare; marital status (married, never married, widowed and divorced); education (less than high-school, high school, technical or junior college, university (4 years), and graduate school), housing tenure (homeowner or not); occupation (regular employee, self-employed, executive officer, part-time/contract employee, full-time homemaker, retired, student and unemployed); and self-rated health (excellent, very good, good, fair, poor).

***Analysis to account for non-response***

The longitudinal approach provides information on individual behavior change. However, a high proportion of respondents may be lost on follow-up, and if their profile differs in important respects from that of respondents who remain in the study, the results may be biased. To account for potential non-random non-response, we applied IPW to the remaining participants in each survey by modeling the probability of not dropping out.

In the follow-up surveys in 2016 and 2017, the questionnaire was e-mailed to individuals who had participated in the previous survey in 2015.1 Subjects who did not respond to the 2016 surveys were nevertheless included in the 2017 follow-up survey. As differences in baseline characteristics between responders and non-responders were observed (data not shown), a logistic regression model was constituted to account for non-response at each wave,9 incorporating potential confounding factors. The Hosmer–Lemeshow tests did not indicate poor fit of the models. Finally, the inverse of the predicted non-dropout probabilities from the logistic models were used as IPWs for each remaining participant to account for the non-responses.10 Samples excluded due to unnatural discrepancies were treated as non-responders.

***Adjustments accounting for both “being an internet survey respondent” and “non-response in the follow-up surveys”***

To fully account for both the use of an internet survey and the attrition at follow-up, we multiplied the IPWs, deriving a final weight for each subject in the 2016 and 2017 surveys, that is, a final weight for responders in the follow-up survey was calculated by multiplying an IPW accounting for internet survey and an IPWaccounting for non-response, after large outliers in each IPW were truncated (max=20 and min=0.05).6 11 For the 2015 estimates, we used only the first IPW. A standardized weight for each year was used to keep the total number of respondents included constant (n=8240). Fully adjusted number, adjusted percentages, and adjusted odds ratios are shown as main results.

***Management of data quality***

To validate data quality, we excluded respondents showing discrepancies and/or artificial/unnatural responses. Because question items were different each survey year, for items such as the number of total household members (2015),1 “Please choose the second from the bottom” (2017) was used, as well as choosing the same number in all of a set of questions (2015, 2016, and 2017) to detect any discrepancies. After exclusion of respondents with any discrepancies in 2015 (n=815, remaining n=8240),1 we further excluded respondents with discrepancies or artificial/unnatural responses in the follow-up surveys (n=37 for 2016; n=87 for 2017).

**Supplementary discussion**

***Symptoms from exposure to secondhand HNB-tobacco aerosol***

6.9% of never-users of both combustible cigarettes and HNB-tobacco/e-cigarettes (“never/never-users”) had been exposed to secondhand HNB-tobacco aerosol. Nearly half of exposed never/never-users answered that they had at least one acute symptom, although these symptoms were not necessarily serious. However, never/never-users accounted for major part of population (51.6% in the present study). If these estimates are simply applied to the total Japanese population (in which the number of adults aged 17–71 years is 86 million, according to the 2015 census), symptoms of whatever kind occurred in approximately 1.5 million people (86,000,000 × 51.6% × 6.9% × 49.2% = 1500,000). Although this result is based on self-reported data, this rate of events is not negligible, and reinforces the need to carefully construct appropriate regulation measures for HNB-tobacco.

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