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Heterogeneity in the association between internet use and dementia among older adults: A machine-learning analysis

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HIGHLIGHTS

- Internet use was associated with dementia among older adults.
- A generalized random forest algorithm flexibly uncovered heterogeneity in the association.
- Multidimensional heterogeneity was observed across income, education, and population density.
- Findings highlight complex heterogeneity missed by traditional analytical methods.

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ABSTRACT

Background & aims: Internet use among older adults may reduce the risk of dementia, but it remains unknown how the effects vary across individuals. The aim of this study was to rigorously examine heterogeneity in the association between internet use and dementia among older adults with a machine learning approach.

Methods: This cohort study used data from the Japan Gerontological Evaluation Study involving functionally independent adults aged 65 or older (n = 5,451). The exposure, internet use a few times a month or more often, was assessed with the 2016 survey (baseline) and covariates (potential confounders and effect modifiers) were assessed with the 2013 survey (pre-baseline). Follow-up continued until 2022, identifying 5.5-year dementia onset (n = 549) using the public long-term care insurance system. Using the generalized random forest algorithm, we estimated how the association between internet use and dementia onset during a 5.5-year follow-up period varies by pre-baseline sociodemographic characteristics and health conditions.

Results: Internet use was on average associated with a lower risk of dementia (estimated population average effect = -0.033; 95 % CI: -0.051, -0.016). However, we found evidence of between-individual heterogeneity in this association, where internet use appeared more beneficial among individuals who reported middle income, higher education levels, and were socially and physically inactive at the pre-baseline wave.

Conclusions: Internet use may disproportionately benefit people based on socioeconomic status, suggesting equity concerns of universal implementation. Understanding such effect heterogeneity can inform more targeted public health interventions.

1. Introduction

Internet use among older adults may play a critical role in maintaining cognitive function (Amini et al., 2019, Berner et al., 2019, Cho et al., 2023, d'Orsi et al., 2018, Green et al., 2021, Kamin and Lang, 2020, Klimova, 2016, Xavier et al., 2014). The internet offers a diverse range of cognitively stimulating activities, including social interactions through video communication platforms or social networking sites, which have been associated with improved cognitive functioning among healthy older adults (Dodge et al., 2015, Myhre et al., 2016). Additionally, internet use provides access to offline experiential opportunities, such as leisure activities and social participation (Nakagomi et al.,

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2022). According to the cognitive reserve hypothesis, these online and offline activities can enhance cognitive stimulation, increase cognitive reserve capacity, and potentially compensate for brain aging, thereby reducing the risk of dementia (Stern, 2002).

The effects of internet use on dementia, however, may differ among various subgroups of older adults. Investigating the sources of this effect heterogeneity is crucial for optimizing resource allocation and maximizing the benefits of internet use in this population. Furthermore, identifying these sources may help address health inequities associated with internet use, as socially advantaged individuals might derive greater benefits. Consequently, a universal promotion of internet use could unintentionally exacerbate existing health disparities.

For instance, older adult cohorts born earlier likely had limited exposure to internet use during their working years compared to later-born cohorts. For these individuals, acquiring internet skills may have been a more cognitively stimulating experience (Kim and Han, 2022). Moreover, research suggests that the cognitive benefits of internet use might vary by gender. Specifically, men may experience a smaller decline in cognitive function through internet use compared to women, possibly due to differences in the types of online activities they pursue (Ihle et al., 2020). Additionally, socioeconomic status is a critical factor, as it can exacerbate inequities in internet skills, (Hargittai et al., 2019) thereby reducing the cognitive benefits of online activities. It may also affect access to subscription-based online resources, further influencing the overall benefits of internet use.

Social surroundings can also influence the effects of internet use on dementia. For example, older adults living alone or facing mobility limitations due to health issues may rely more on internet use to sustain their social connections (Cotten, 2021). These individuals might obtain greater cognitive stimulation from internet use compared to those with access to alternative forms of social engagement (Kim and Han, 2022).

While these studies offer valuable preliminary evidence, they have two notable limitations. First, prior research has primarily employed a deductive approach, in which a limited set of variables is pre-selected a priori as potential sources of effect heterogeneity. Second, conventional analytic methods, such as subgroup analyses or the inclusion of interaction terms for treatments and moderators, often fail to simultaneously account for multiple effect modifiers. The interplay of various factors—such as gender, education, and living arrangement—can jointly shape the effects of internet use in a synergistic manner, as suggested by intersectionality theory (Alvidrez et al., 2021).

To our knowledge, no study has rigorously examined the heterogeneity in the association between internet use and dementia among older adults. To address this gap, we employed a machine-learning algorithm—the generalized random forest (GRF)—to flexibly and inductively assess heterogeneity in the relationship between internet use and dementia within a cohort of older adults in Japan (Jawadekar et al., 2023, Shiba and Inoue, 2024).

2. Methods

2.1. Data

We utilized data from the Japan Gerontological Evaluation Study (JAGES), a nationwide survey targeting functionally independent older adults in Japan. Self-administered questionnaires were distributed to adults aged 65 years or older who were not receiving benefits from public long-term care insurance (LTCI) in both 2013 and 2016. Japan's universal health care system ensures that all citizens have access to medical services. Additionally, individuals aged 65 and older are automatically enrolled in the LTCI program, which provides support for older adults with disabilities. Notably, those who were not receiving LTCI benefits at the baseline evaluation were likely individuals without cognitive disabilities. We constructed analytic samples by linking baseline respondents to the national Long-Term Care Insurance (LTCI) database, which provides dementia certification data through administrative records. This linkage allowed for a high follow-up rate of 98.2 %, minimizing attrition bias. Finally, to reduce the risk of positivity violation, we removed individuals with extreme values of the estimated propensity scores ($<$0.1 or $>$0.9) (Crump et al., 2009). This resulted in the analytic sample of 5,451 individuals (Supplementary Figure 1, 2).

2.2. Measurement

2.2.1. Outcome

The development of cognitive disability (dementia) during the follow-up period (2016–2022) was tracked through linkage to registries maintained by local municipal governments and recorded under the Japanese LTCI system (See Supplementary Methods) (Hikichi et al., 2019). Applicants requesting long-term care were assessed for eligibility by trained investigators specializing in the evaluation of activities of daily living (ADL), instrumental activities of daily living (IADL), cognitive function, and mental and behavioral disorders, following a standardized protocol. Cognitive and functional disabilities were identified through the LTCI certification process. The details of the assessment criteria and the definition of dementia are provided in Supplementary Table 1. To maintain a consistent follow-up duration across all participants, we excluded follow-up periods exceeding 5.5 years to align with the minimum follow-up duration set by the municipalities.

2.2.2. Exposure

Our exposure variable, internet use, was derived from the 2016 survey. Participants were asked, "Have you used the Internet or e-mail in the past year?" with response options of "no," "a few times a month," "a few times a week," and "almost every day." Our previous study revealed a trend indicating a lower risk of dementia among individuals who used the internet a few times a month or more frequently compared to non-users (Nakagomi et al., 2022). In this analysis, internet use was categorized into two groups: non-users and users (defined as those who used the internet a few times a month or more).

2.2.3. Covariates

We selected 31 pre-exposure variables from the 2013 survey, including 2 demographic characteristics, 5 measures of socioeconomic status, 6 measures of social relations, 10 health conditions, 3 measures of higher-level functional capacity, and 5 behavioral factors (see Supplementary Table 2 for the complete list of selected variables). These factors were chosen because they were likely to act as confounders, effect modifiers, or both.

2.3. Statistical analysis

2.3.1. Estimating population average treatment effects (ATEs)

First, we calculated the population average treatment effects (ATEs) of internet use on the onset of dementia over the 5.5-year follow-up period. ATEs quantify the risk difference and risk ratio of dementia under the hypothetical scenarios where everyone in the population had used the internet versus if no one had used it. To estimate ATEs, we applied the doubly robust targeted maximum likelihood estimation (TMLE) method. This approach simultaneously models both the exposure and outcome, ensuring consistent ATE estimates as long as at least one of the models is correctly specified. As a result, TMLE is more robust to bias arising from model misspecification.

Both models were fitted data-adaptively using the SuperLearner, an ensemble learning method that integrates multiple candidate estimators, such as generalized linear models, gradient-boosting machines, and neural networks (Schuler and Rose, 2017). Targeted maximum likelihood estimation and Super Learning were implemented using the **ltmle** and **SuperLearner** R packages (R Foundation for Statistical Computing, Vienna, Austria).

2.3.2. Examine heterogeneity in the association between internet use and dementia

We estimated the conditional average treatment effects (CATEs) of internet use on dementia. CATE represents the effect of an exposure conditional on the values of a set of covariates (L = l):

$$E[Y_{a=1} - Y_{a=0}|L = l]$$

where Y_a is the potential outcome Y under the binary treatment A = a.

We estimated CATEs and identified potential sources of effect heterogeneity using the causal forest approach from the generalized random forest (GRF) algorithm (Athey et al., 2019). Causal forest extends the random forest algorithm, a widely used nonparametric method for predicting conditional expectations. In the standard random forest framework, multiple regression trees are grown by partitioning bootstrapped subsamples based on randomly selected subsets of covariates. Each tree assigns individuals with similar covariate values to the same leaf and computes a weighted average of the outcome within that leaf. Unlike standard random forests, which predict average outcomes, causal forests estimate contrasts in outcomes between exposed and unexposed individuals within each leaf, thereby identifying CATEs. To adjust for confounding, residualization was performed using 31 observed pre-exposure covariates. While each tree was constructed using a random subset of covariates, the final CATE estimates were derived as weighted averages of predictions across all trees. As a result, the estimates can be interpreted as conditional on all 31 covariates (Nie and Wager, 2021).

When growing trees, the causal forest algorithm randomly splits each subsample into two halves: one half is used to determine the partitioning structure, while the other half is used to estimate CATEs within each leaf. This approach, known as "honesty," helps mitigate bias in tree predictions by ensuring that the same data are not used for both partitioning and estimation. The partitioning process is specifically designed to maximize heterogeneity in treatment effect estimates across the leaves, thereby improving the identification of effect modifiers. We implemented the GRF method using the **grf** package in R (R Foundation for Statistical Computing). To enhance the robustness of our estimates, we employed 10-fold cross-fitting, ensuring that predictions for each fold were based on trees trained without any observations from that fold. This procedure further reduces overfitting and enhances generalizability.

Before constructing a causal forest with 2,000 regression trees for the outcome, we utilized out-of-bag samples to fine-tune model parameters through cross-validation. The parameters optimized included the fraction of data used to build each tree, the number of variables considered for each split, the minimum number of observations required in each leaf, the fraction of data used for determining splits, whether pruning should be applied to prevent empty leaves in the estimation sample, the maximum allowable imbalance in a split, and the penalty for imbalanced splits. To ensure the reproducibility of our analysis, we provide the R code used for this process in **Supplementary Method**.

To evaluate the model performance and formally test for the presence of effect heterogeneity, we conducted two analyses. First, we implemented a "best linear predictor" (BLP) analysis (Chernozhukov et al., 2018). The BLP analysis fits the following model:

$$Y_i - \widehat{Y}_i = \alpha(A_i - p(L_i))\cdot\overline{\tau} + \beta(A_i - p(L_i))(\widehat{\tau}_i - \overline{\tau}) + \varepsilon$$

where $\widehat{\tau}_i$ is the predicted CATE for individual i, $\overline{\tau}$ is the mean of the CATE estimates, $\widehat{Y}_i$ is the predicted outcome, and p(L) = Pr[A = 1|L] is the probability of internet use conditional on the covariates. If the coefficient α (the mean forest) is close to 1, it indicates that the average forest prediction is well calibrated. If the coefficient β (the differential forest) is close to 1, it suggests that the forest prediction captures the underlying heterogeneity effectively. The one-sided test of β > 0 serves as an omnibus test for effect heterogeneity.

Second, to further assess if the causal forest model correctly captured the effect heterogeneity underlying the data, we estimated sorted group average treatment effects (GATEs) (Chernozhukov et al., 2018). Specifically, we ranked each individual in each fold based on their CATE estimates and grouped these ranks into quintiles (as the ranks were specific to each of the 10 folds, there were 10 ties for each rank). We then used TMLE to estimate the ATEs for each of the CATE quintile groups. With a well-calibrated forest, we expect the GATE estimate to increase monotonically across quintiles defined by the CATE ranks.

2.3.3. Explore the sources of effect heterogeneity

First, we ranked each individual within each fold based on their estimated CATEs, grouped these ranks into quintiles, and calculated the means and proportions of covariates stratified by the estimated CATE quintiles. To assess differences across the five CATE groups, we conducted ANOVA for continuous variables and Chi-Square tests for categorical variables.

Second, we identified key predictors of effect heterogeneity using the "variable importance" feature of the GRF algorithm. Variable importance was determined by counting how frequently each variable was used to split the data during the construction of the causal forest model. Specifically, the variable importance score represents the percentage of trees in which a given covariate contributed to sample partitioning.

Lastly, we generated heatmaps showing the estimated CATEs varied by levels of the combinations of multiple covariates, including: the top 3 variables in the variable importance ranking, and according to the levels of age, gender, and the top ten ranked variables of "variable importance".

2.3.4. Population attributable fraction (PAF)

To assess the potential public health impact of internet nonuse on dementia risk, we estimated the PAF. This calculation assumes that the observed risk ratios reflect causal effects and that the sample is representative of the broader older adult population in Japan. While subject to limitations, the PAF offers a crude but useful measure for comparing the potential contribution of risk factors to disease burden at the population level.

We performed imputation of missing data using random forest via the R (R Foundation for Statistical Computing) package "**missRanger**". All analyses were performed using R, version 4.4.0.

3. Results

During the follow-up period, 549 of 5,451 (10.0 %) developed dementia. Among internet users and non-users, 158 of 2413 (6.5 %) and 391 of 3,038 (12.9 %) developed dementia. Table 1 summarizes the baseline characteristics of the analytic sample based on internet usage. Internet users tended to be younger and were more likely to come from higher socioeconomic status backgrounds, including higher levels of education, income, and wealth. Additionally, they were more likely to be employed and married.

The estimated risks of dementia among internet users and non-users, as derived from TMLE, were 0.081 (95 % CI: 0.067–0.094) and 0.114 (95 % CI: 0.103–0.125), respectively. The population average treatment effect (ATE) of internet use on dementia onset was –0.033 (95 % CI: –0.051 to –0.016), corresponding to a risk ratio of 0.71 (95 % CI: 0.58–0.86). The inverse, indicating the risk ratio for internet nonuse, was 1.41 (95 % CI: 1.16–1.72). The population attributable fraction (PAF) of internet nonuse for dementia was estimated at 18.6 % (95 % CI: 8.3–28.7 %).

Fig. 1 illustrates the distribution of CATEs estimated using the GRF. The majority of CATEs were below zero, aligning with the ATE estimates. However, the distribution was broad (standard deviation: 0.021), indicating effect heterogeneity. We found evidence of heterogeneity across three different approaches. First, the estimated coefficient from the BLP for the differential forest prediction was 0.955 (p = 0.027),

Table 1
Baseline characteristics of imputed data in JAGES.

	Total (N = 5451)	Non-user (N = 3038)	User (N = 2413)
Age, mean (SD)	72.2 (4.97)	73.2 (5.05)	71.0 (4.58)
Gender, n(%)			
Men	2523 (46.3 %)	1359 (44.7 %)	1164 (48.2 %)
Women	2928 (53.7 %)	1679 (55.3 %)	1249 (51.8 %)
Education, n(%)			
<9 years	1790 (32.8 %)	1305 (43.0 %)	485 (20.1 %)
10-12 years	2388 (43.8 %)	1224 (40.3 %)	1164 (48.2 %)
13- years	1273 (23.4 %)	509 (16.8 %)	764 (31.7 %)
Household equivalized income (million yen), mean (SD)	243 (138)	220 (129)	271 (143)
Wealth, n(%)			
-50 ten thousand yen	164 (3.0 %)	114 (3.8 %)	50 (2.1 %)
50-100 ten thousand yen	168 (3.1 %)	113 (3.7 %)	55 (2.3 %)
100-500 ten thousand yen	699 (12.8 %)	447 (14.7 %)	252 (10.4 %)
500-1000 ten thousand yen	818 (15.0 %)	508 (16.7 %)	310 (12.8 %)
1000-5000 ten thousand yen	2881 (52.9 %)	1549 (51.0 %)	1332 (55.2 %)
5000- ten thousand yen	721 (13.2 %)	307 (10.1 %)	414 (17.2 %)
Employment status, n(%)			
Working	1306 (24.0 %)	657 (21.6 %)	649 (26.9 %)
Retired	3674 (67.4 %)	2059 (67.8 %)	1615 (66.9 %)
Never worked	471 (8.6 %)	322 (10.6 %)	149 (6.2 %)
Population density, mean (SD)	6770 (3670)	6370 (3690)	7270 (3590)
Marital status, n(%)			
Married	4213 (77.3 %)	2284 (75.2 %)	1929 (79.9 %)
Bereaved	913 (16.7 %)	565 (18.6 %)	348 (14.4 %)
Divorced	168 (3.1 %)	86 (2.8 %)	82 (3.4 %)
Single	122 (2.2 %)	80 (2.6 %)	42 (1.7 %)
Other	35 (0.6 %)	23 (0.8 %)	12 (0.5 %)
Living arrangement, n(%)			
Living with someone	4750 (87.1 %)	2628 (86.5 %)	2122 (87.9 %)
Living alone	701 (12.9 %)	410 (13.5 %)	291 (12.1 %)

which is close to 1 (Supplementary Table 3). Second, the calibration plot showed a monotonic increase in the rank-specific ATE estimate across the CATE ranking (Supplementary Figure 3).

Table 2 shows the means (standard deviation) or numbers (proportions) of the variables across the quintiles of the CATE. Several covariates exhibited consistent upward or downward trends from the first to the fifth quintile of the CATE. For instance, individuals with higher CATEs (indicating that internet use is more effective) were older, had higher educational attainment, had lower incomes, were more likely to be married, had less social participation, had fewer meetings with friends, and walked less. Conversely, some covariates did not follow a monotonic trend and peaked at quintile 2, 3, or 4, such as population density, body mass index, Geriatric Depression Scale scores, and gender.

The ranking of the importance of variables in the causal forest model is displayed in Supplementary Figure 4. The most significant variables are household equivalized income, population density, education, and

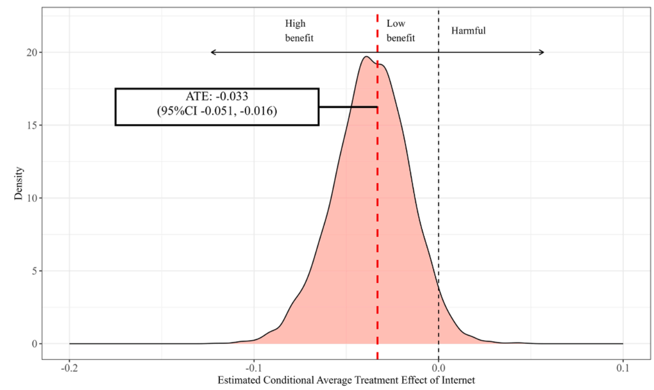

Fig. 1. Distributions of estimated conditional average treatment effects of internet use on dementia.
Abbreviations: ATE, average treatment effects; CI, confidence interval.
Average treatment effect was estimated via Targeted Maximum Likelihood Estimation.

age, each with high importance values close to 0.08. There is a notable decline in importance after the top 20 variables, especially after hypertension.

Lastly, we created heatmaps illustrating the distributions of estimated CATEs across combinations of the top three ranked variables: household income, population density, and education (Fig. 2). This heatmap highlighted complex, high-dimensional heterogeneity, indicating the greatest CATE among individuals with equivalized income of 159-224 ten thousand yen, living in areas with population density ranged from 5480 to 9610 /km2, and with high educational attainment while the lowest CATE among individuals with equivalized income of 228–1300 ten thousand yen and with low educational attainment. Additionally, we created heatmaps illustrating the distributions of estimated CATEs across combinations of age, gender, and nine variables from the top ten rankings (Supplementary Figure 5). For instance, the internet may be more beneficial for those aged 72–91 who are less active, such as those who participated in social activities less than once a week, walked less than 30 min a day, and met friends less than once a week. Furthermore, the internet may be more effective for married men and women aged 72–91.

4. Discussion

We estimated the heterogeneous treatment effects of internet use on dementia and found three main results. First, after adjusting for a set of 31 characteristics, there was strong evidence of population average effects of internet use on dementia onset over a 5.5-year follow-up period. Second, we identified significant heterogeneity in the associations between internet use and dementia, as evidenced by the wide distribution of the estimated CATEs and the results of three tests for effect heterogeneity. Third, we inductively identified patterns in the characteristics of subgroups particularly affected by internet use. For instance, the association between internet use and dementia was stronger among individuals characterized by middle income, medium population density area, and simultaneously high educational attainment. Additionally, older individuals, women, and those with lower social engagement (e.g., less social participation and fewer meetings with friends) were more likely to experience the positive effects of internet use.

Our findings on the population average effects of internet use on dementia are consistent with previous observational studies (Amini et al., 2019, Berner et al., 2019, Cho et al., 2023, d'Orsi et al., 2018, Green et al., 2021, Kamin & Lang, 2020, Klimova, 2016, Xavier et al., 2014). Our previous study with three-year follow-up on the same cohort in Japan also showed similar trends, although not significant, with risk ratios ranging from 0.69 to 0.85 for individuals who used the internet

Table 2
Characteristics across the quintiles of the CATE.

	High benefit <——— Ranking ———> Low benefit					
	1 (n = 1,095)	2 (n = 1,089)	3 (n = 1,086)	4 (n = 1,089)	5 (n = 1,092)	p_value
CATE estimates	-0.065 (0.011)	-0.047 (0.004)	-0.036 (0.004)	-0.026 (0.004)	-0.009 (0.01)	> 0.001
Age	74.8 (4.7)	72.8 (4.6)	71.5 (4.6)	70.9 (4.8)	71.1 (5.0)	> 0.001
Gender (Men)	376 (34.3 %)	485 (44.5 %)	563 (51.8 %)	563 (51.7 %)	536 (49.1 %)	> 0.001
Education: <9 years	244 (22.3 %)	308 (28.3 %)	361 (33.2 %)	387 (35.5 %)	490 (44.9 %)	> 0.001
Education: 9-12 years	457 (41.7 %)	502 (46.1 %)	477 (43.9 %)	488 (44.8 %)	464 (42.5 %)	0.244
Education: 13- years	394 (36.0 %)	279 (25.6 %)	248 (22.8 %)	214 (19.7 %)	138 (12.6 %)	> 0.001
Equivalized income	214.8 (99.8)	220.3 (120.4)	234.1 (135.6)	254.8 (148.8)	290.2 (161.8)	> 0.001
Wealth (1: -50, 6: 5000- ten thousand yen)	4.7 (0.9)	4.6 (1.1)	4.4 (1.2)	4.4 (1.2)	4.5 (1.3)	> 0.001
Employment: working	64 (5.8 %)	160 (14.7 %)	247 (22.7 %)	367 (33.7 %)	468 (42.9 %)	> 0.001
Employment: retired	882 (80.5 %)	833 (76.5 %)	749 (69 %)	659 (60.5 %)	551 (50.5 %)	> 0.001
Employment: never worked	149 (13.6 %)	96 (8.8 %)	90 (8.3 %)	63 (5.8 %)	73 (6.7 %)	> 0.001
Population density	6789.1 (3097.1)	6377.6 (3427.6)	6581.1 (3641.4)	6844.1 (3996.3)	7250.3 (4057.3)	> 0.001
Marital status: married	967 (88.3 %)	896 (82.3 %)	891 (82.0 %)	784 (72.0 %)	675 (61.8 %)	> 0.001
Marital status: widowed	107 (9.8 %)	146 (13.4 %)	143 (13.2 %)	217 (19.9 %)	300 (27.5 %)	> 0.001
Marital status: divorced	10 (0.9 %)	27 (2.5 %)	28 (2.6 %)	42 (3.9 %)	61 (5.6 %)	> 0.001
Marital status: single	7 (0.6 %)	15 (1.4 %)	18 (1.7 %)	34 (3.1 %)	48 (4.4 %)	> 0.001
Marital status: other	4 (0.4 %)	5 (0.5 %)	6 (0.6 %)	12 (1.1 %)	8 (0.7 %)	0.217
Living alone	84 (7.7 %)	125 (11.5 %)	118 (10.9 %)	167 (15.3 %)	207 (19 %)	> 0.001
Meeting with friends (1:never, 6:almost every day)	3.6 (1.5)	3.7 (1.5)	3.8 (1.5)	3.9 (1.6)	4.2 (1.6)	> 0.001
Frequency of participation a week	1.6 (3.1)	1.7 (3)	1.9 (3.1)	1.8 (3)	2.5 (3.4)	> 0.001
No instrumental social support	45 (4.1 %)	50 (4.6 %)	37 (3.4 %)	51 (4.7 %)	64 (5.9 %)	0.086
No emotional social support	45 (4.1 %)	49 (4.5 %)	45 (4.1 %)	58 (5.3 %)	56 (5.1 %)	0.542
Self-rated health	2.9 (0.5)	3 (0.5)	3 (0.5)	3 (0.5)	3.1 (0.6)	> 0.001
Body mass index	22.7 (3)	23.3 (3.1)	23.1 (3.1)	23.1 (3.2)	22.6 (3.1)	> 0.001
Geriatric depression scale	3.1 (2.8)	3.2 (3)	2.7 (2.7)	2.7 (2.6)	2.4 (2.5)	> 0.001
No disease treated	74 (6.8 %)	123 (11.3 %)	183 (16.9 %)	250 (23 %)	429 (39.3 %)	> 0.001
Hypertension	520 (47.5 %)	542 (49.8 %)	473 (43.6 %)	468 (43 %)	361 (33.1 %)	> 0.001
Diabetes	140 (12.8 %)	154 (14.1 %)	149 (13.7 %)	142 (13.0 %)	89 (8.2 %)	> 0.001
Stroke	27 (2.5 %)	30 (2.8 %)	27 (2.5 %)	17 (1.6 %)	15 (1.4 %)	0.092
Depression	19 (1.7 %)	10 (0.9 %)	4 (0.4 %)	2 (0.2 %)	2 (0.2 %)	> 0.001
Vision diseases	192 (17.5 %)	209 (19.2 %)	192 (17.7 %)	175 (16.1 %)	161 (14.7 %)	0.064
Hearing diseases	61 (5.6 %)	63 (5.8 %)	44 (4.1 %)	56 (5.1 %)	44 (4.0 %)	0.168
Instrumental activities	4.9 (0.4)	4.9 (0.5)	4.9 (0.4)	4.9 (0.4)	4.9 (0.4)	0.347
Intellectual activity	3.7 (0.6)	3.7 (0.6)	3.7 (0.6)	3.7 (0.5)	3.8 (0.5)	> 0.001
Social role	3.2 (1.0)	3.3 (1.0)	3.4 (0.9)	3.4 (0.9)	3.5 (0.8)	> 0.001
Smoking	66 (6.0 %)	73 (6.7 %)	129 (11.9 %)	122 (11.2 %)	130 (11.9 %)	> 0.001
Alcohol consumption	264 (24.1 %)	383 (35.2 %)	471 (43.4 %)	494 (45.4 %)	492 (45.1 %)	> 0.001
Going out (1: less than once a week, 3: almost everyday)	2.6 (0.5)	2.8 (0.5)	2.8 (0.4)	2.9 (0.4)	2.9 (0.3)	> 0.001
Walking Time (1: -30 min a day, 4: 90 min a day)	2.1 (1.0)	2.2 (1.0)	2.4 (1.0)	2.5 (1.0)	2.8 (1.0)	> 0.001
Hobby	95 (8.7 %)	93 (8.5 %)	79 (7.3 %)	72 (6.6 %)	64 (5.9 %)	0.051

CATE: Conditional Average Treatment Effects

from a few times a month to almost every day (Nakagomi et al., 2022). This present study utilized data from a 5.5-year follow-up period, comparable to other studies, thus providing evidence on the association between internet use and dementia among older adults in Japan.

The impact of internet use on dementia risk, if interpreted causally, may have substantial implications for public health. The risk ratio of 1.41 for internet nonuse is comparable to those of established modifiable dementia risk factors in later life such as smoking (1.6), physical inactivity (1.4), and social isolation (1.6) (Ballard, 2020). Furthermore, the PAF for internet nonuse was estimated at 18.6 %, which exceeds the corresponding PAFs for smoking (14.1 %), physical inactivity (4.2 %), and social isolation (9.6 %) (Ballard, 2020). Given that internet penetration among older adults in Japan remains low—only 65.5 % in their 70s and 33.2 % in their 80s as of 2022 (Ministry MoIAaC, 2024)—addressing the digital divide could have a meaningful impact on reducing dementia incidence at the population level.

Our study also identified subgroups for whom internet use was associated with a substantially lower risk of dementia compared to the population average. Only a few studies have explored effect heterogeneity on the association between internet use and dementia. Moreover, these studies that assess effect heterogeneity rely on a deductive approach, where researchers select a limited set of predictors—typically one or a few—a priori as potential sources of effect heterogeneity and then statistically test interactions one variable at a time (Cho et al., 2023, Ihle et al., 2020, Kim & Han, 2022). The inductive approach used in our study, utilizing GRF, is advantageous because it does not require researchers to specify effect modifiers in advance. Instead, it identifies them from a large set of candidates in a data-driven manner.

Our approach demonstrates complex, high-dimensional heterogeneity characterized by greater impacts among people with middle income, medium population density, and high educational attainment. With moderate income, individuals can afford a variety of internet-enabled devices and services that offer cognitive stimulation. These services are more available in medium population density areas than in low-density areas. Additionally, individuals with higher education levels are more likely to engage in complex cognitive activities online and utilize both online and offline resources effectively due to greater digital literacy (Arias López et al., 2023). Conversely, high-income individuals with low education may not use the internet as effectively for cognitive engagement. While they have the financial means, they often lack the necessary skills or knowledge to maximize the benefits of internet usage. These individuals might rely more on traditional methods and services (e.g., hiring professionals for tasks they could do online) rather than leveraging online resources, especially if they lack the skills. These findings suggest that addressing health inequities based on internet use inequalities by socio-economic status is not simple. Universal promotion of internet and smartphone use among older adults could either widen or narrow health inequities by income, population density, and education. While promoting digital engagement is beneficial, targeted strategies might be necessary to ensure that the benefits of

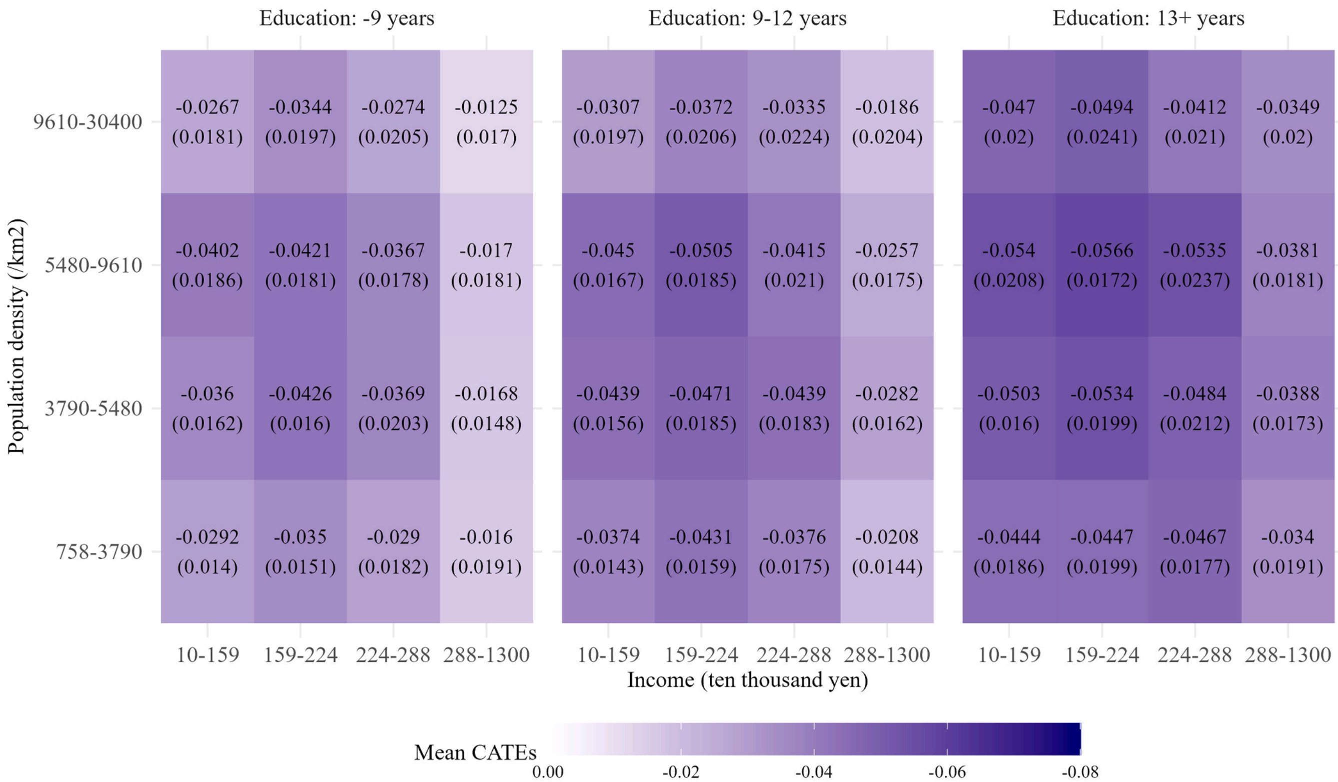

Fig. 2. Heatmaps showing the distribution of estimated conditional average treatment effects of internet use on dementia stratified by top 3 rank variables. CATE: Conditional Average Treatment Effects.

internet use are equitably distributed across different socioeconomic groups.

Our inductive approach for assessing effect heterogeneity provided potentially new insights that could have been missed with a deductive approach, that is the potential benefits of internet use for dementia among older adults who are less socially and physically active. This is illustrated by factors such as less social participation, less social interaction, less walking, having fewer social roles, being retired, and going out less frequently. A similar finding is reported in a cross-sectional study showing lower cognitive function among internet non-users with social isolation compared to users with social isolation (Li et al., 2022) although evidence is quite scarce. Our study extends beyond existing knowledge. There are two potential mechanisms for this effect: via online activities and offline activities. First, individuals who are less active in the real world may be more stimulated by online activities, such as information seeking, instrumental use, and social connections over remote distances. Second, the internet may act as a coping mechanism in response to late-life social challenges (Elliot et al., 2013). Thus, internet use may provide less active older adults with greater opportunities for social engagement in the real world, (Nakagomi et al., 2022) which in turn can help prevent the onset of dementia (Nakagomi et al., 2023).

Four limitations should be noted. First, our ATE and CATE estimates rely on the assumption that adjustment for the 31 observed covariates adequately controls for confounding in the exposure–outcome relationship. However, this assumption may not hold if there are unmeasured or residual confounders, which could bias the estimated associations. Second, our binary measure of internet use—categorized as “a few times a month or more” versus “none”—was relatively crude and may not capture meaningful variation in engagement. Important dimensions such as frequency, duration, purpose, and quality of internet use were not assessed, potentially obscuring more nuanced associations with dementia risk. Moreover, this categorization reflects a methodological constraint of the generalized random forest approach, which currently requires binary exposure variables. Future research should explore more granular assessments of internet behavior to better understand how specific patterns of use relate to cognitive health and its heterogeneity. Third, selective attrition due to loss to follow-up may introduce selection bias, particularly if individuals with early cognitive decline are less likely to remain in the study. However, this concern is mitigated by our use of administrative data from the LTCI system, which enabled follow-up for 98.2 % of participants. This high follow-up rate reduces the likelihood of substantial attrition-related bias. Fourth, our dementia outcome was based on long-term care insurance data, which captures only cases severe enough to require care services. Milder or undiagnosed cases may have been missed, potentially introducing detection bias and limiting the generalizability of our findings to individuals with more advanced dementia. Fifth, some of the observed patterns from our inductive approach are inconclusive and may be due to chance. Future studies should test specific hypotheses with a deductive approach to better understand the mechanisms underlying effect heterogeneity. Lastly, the generalizability of our findings may be limited to the Japanese context, as patterns of internet use, available resources, and social norms around aging differ across countries. Caution is needed when applying these results to other cultural settings.

In conclusion, our study provided evidence of significant heterogeneity in the impacts of internet use on dementia onset among older adults in Japan. We identified subpopulations that particularly benefit from internet use in terms of dementia prevention and uncovered complex and multidimensional heterogeneity, particularly by socioeconomic status such as income, residential area, and education. Moreover, we found that socially and physically inactive individuals may benefit more from internet. These findings would likely have been overlooked if we had only estimated the population average effects or used a conventional deductive approach to assess effect heterogeneity. Understanding such effect heterogeneity can inform more targeted public health interventions, such as smartphone lectures for older adults, to reduce health inequities caused by the digital divide.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI) to refine the readability and language of the manuscript. After using this tool, the authors carefully reviewed and edited the content as needed and take full responsibility for the accuracy and integrity of the published article.

CRediT authorship contribution statement

Atsushi Nakagomi: Writing – original draft, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Katsunori Kondo:** Writing – review & editing, Resources, Investigation. **Koichiro Shiba:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.archger.2025.105912.

Data availability

Data are from the JAGES study. All enquiries are to be addressed at the 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 the human participants.

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