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Mapping social health and dementia risk: A register-based study of older adults in Finland

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ABSTRACT

This study investigates the role of individual and area-level social health factors in shaping geographic variation in dementia incidence among older adults in Finland.

Using nationwide register data on all individuals born between 1935 and 1939 and residing in Finland in 2015 (N = 185,712), we estimate cumulative dementia incidence over a four-year follow-up period (2016-2019). To reduce compositional bias in geographical comparison, we applied Matching on poset-based Average Rank for Multiple Treatments (MARMoT), a non-parametric matching approach that balances observed individual level characteristics across municipalities. Spatial scan statistics were then used to identify geographic clusters of excess dementia incidence considering municipality-level contextual measures after adjustment for individual-level characteristics.

Before MARMoT adjustment, several contiguous clusters of elevated dementia incidence were identified, particularly in eastern and southern Finland, with the highest risk cluster exhibiting a 36% higher incidence than the rest of the country. After balancing individual-level characteristics, some clusters attenuated, whereas others persisted or newly emerged, suggesting a confounding role of individual characteristics in the relationship between dementia incidence and place of residence. Excess incidence remained in parts of eastern Finland (21% - 51% excess risk) and emerged in west-central municipalities (27% excess risk). The inclusion of municipality-level indicators did not substantially alter these patterns.

These findings underscore the importance of accounting for social health and socio-demographic composition in spatial analysis of dementia and demonstrate the value of integrating matching-based and spatial methods to distinguish compositional from contextual disparities in ageing societies.

1. Introduction

Maintaining cognitive functioning in later life is a fundamental condition for autonomy and quality of life, and dementia represents one of the most pressing public health challenges in ageing societies. Globally, over 57 million people live with dementia, with nearly 10 million new diagnoses each year, making it the seventh leading cause of death and a major contributor to disability among older adults (World Health Organization, 2021).

While dementia is often perceived as an inevitable consequence of ageing, a growing body of research reveals substantial social and geographic disparities in its incidence and prevalence (Crimmins et al., 2018; Hudomiet et al., 2022). These inequalities reflect not only biological vulnerability, but also differences in individuals' social resources and the environments in which they age. Socioeconomic status and family structure are important individual-level factors associated with dementia risk and patterns of diagnosis (Brayne et al., 2006; Jones, 2017; Luth and Prigerson, 2022). At the same time, contextual factors

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such as neighbourhood characteristics, service availability, and broader features of social environment have been linked to cognitive decline and dementia (Antonucci et al., 2024; Clarke et al., 2015).

As a result, there is growing recognition that dementia should be examined not only through traditional biomedical and psychological models, but also within a broader framework that accounts for social conditions and environmental exposures across the life course (Downs, 2000; Winblad et al., 2016).

Within this broader perspective, the concept of *social health* has gained increasing attention as a framework for understanding how social conditions shape cognitive ageing and dementia risk. Already introduced by the World Health Organization (WHO) in 1946 as one of the three core dimensions of health, social health refers to individuals' capacity to participate in social life, engage in meaningful relationships, and preserve autonomy within their social environment (Vernooij-Dassen et al., 2018; Vernooij-Dassen and Jeon, 2016; World Health Organization, 1946). Empirically, social health has often been operationalized through indicators of social engagement, such as participation in social activities, frequency of contact with others, or perceived social support. These dimensions capture important behavioural and subjective aspects of social life and have been consistently associated with cognitive outcomes (Bellou et al., 2017; Lenart-Bugla et al., 2022). Individuals with higher levels of social engagement, frequent interpersonal contact, and participation in cognitively stimulating activities tend to experience more favourable cognitive outcomes and a lower risk of developing dementia, whereas social isolation has been associated with accelerated cognitive decline and increased dementia incidence, particularly in later life (Duffner et al., 2022; Freak-Poli et al., 2022; Joyce et al., 2022; Kuiper et al., 2015; Ma et al., 2018; Maddock et al., 2023; Marseglia et al., 2023; Piolatto et al., 2022; Samtani et al., 2022; Sommerlad et al., 2019; Sutin et al., 2020; Tsutsumimoto et al., 2017; Van Der Velpen et al., 2022).

More recent conceptualizations expand the notion of social health beyond observed social behaviours, framing it as a broader construct that encompasses the structural and relational conditions shaping individuals' opportunities for engagement, support, and autonomy across the life course (Vernooij-Dassen et al., 2018, 2021; Vernooij-Dassen and Jeon, 2016). From this perspective, the concept of social health may not be limited to enacted participation but also includes the underlying social resources that enable or constrain such participation. Partnership status and partnership histories, parenthood and family ties, as well as proximity to kin, constitute foundational social resources, particularly in later life when health limitations or major life-course transitions may restrict active engagement. These structural and relational conditions can influence dementia risk through mechanisms related to cognitive reserve, defined as the brain's resilience to neuropathological damage (Hahn and Lee, 2019; Livingston et al., 2020; Penninkilampi et al., 2018).

Importantly, social health extends beyond individual ties to encompass the broader social environment in which individuals are embedded. Contextual features such as the availability of local support services, social infrastructure, and neighbourhood characteristics shape structural opportunities for interaction, reciprocity and access to resources over time (Clarke et al., 2015; Finlay et al., 2021; Michael and Yen, 2014; Wu et al., 2015). Environments that enable sustained social engagement can reinforce cognitive reserve, whereas socially deprived or exclusionary contexts may constrain access to support and increase vulnerability to cognitive decline.

Additionally, dementia risk is shaped not only by isolated social exposures but by the cumulative patterning of social advantages and disadvantages. Empirical evidence shows that co-occurring social vulnerabilities, such as social isolation, economic hardship, limited participation, and weak social ties, are associated with increased dementia risk. In contrast, the joint presence of protective resources, including higher education, occupational complexity, and sustained social engagement, is associated with greater cognitive resilience and a reduced likelihood of decline (Ma et al., 2018; Opdebeeck et al., 2018; Saito et al., 2018; Tsutsumimoto et al., 2017; Vernooij-Dassen et al., 2021; Wang et al., 2017; Yang et al., 2018).

Examining dementia through a spatial lens introduces an additional layer of analytical complexity. Social advantages and disadvantages are not randomly distributed across areas but tend to cluster geographically as a result of long-term demographic, socio-economic, and institutional processes. Selective migration and residential immobility may further reinforce these patterns: individuals in poorer health or with fewer resources may be less able to relocate, while healthier or more advantaged individuals may concentrate in areas with better services and infrastructures.

As a result, geographic differences in dementia incidence may reflect two intertwined mechanisms: compositional effects (who lives in an area) and contextual effects (what the area is like). When municipalities differ substantially in their socio-demographic and health profiles, standard regression adjustment may not fully ensure comparability, and observed spatial differences may still reflect residual compositional heterogeneity. Distinguishing between these mechanisms is essential not only for methodological clarity but also for policy relevance, as it informs whether interventions should primarily target individual-level vulnerabilities, place-based conditions, or their interaction.

To address this challenge, we adopt a dual-level analytical framework that accounts for both individual and area-level contributions to dementia risk. We focus on Finland, a country characterized by a universalistic Nordic welfare regime and exceptionally high-quality population registers. These data enable the observation of stable structural and relational dimensions of social health at the individual level for the entire population, including detailed information on family status, proximity to kin, socio-economic background, and area of residence. The longitudinal nature of the registers allows us to examine population-level patterns of cognitive vulnerability while minimizing recall bias and selective attrition common in survey-based research.

This study adopts a register-based operationalization of social health, focusing on structural and relational social resources observable in administrative data. Rather than capturing enacted social behaviours or subjective experiences, such indicators reflect enduring social conditions, such as partnership status, parenthood, geographic proximity to kin, and exposure to widowhood, that may shape access to support and role continuity in later life.

To address covariate imbalance and potential compositional confounding across municipalities, we employ the Matching on poset-based Average Rank for Multiple Treatments (MARMoT) approach (Silan et al., 2021), a non-parametric method designed to achieve covariate balance simultaneously across multiple groups (here, 230 municipalities). MARMoT constructs a reweighted synthetic population in which individual-level characteristics are balanced across areas, thereby enabling the estimation of geographic differences net of observed compositional variation.

Following covariate balancing, we apply spatial scan statistics to identify contiguous clusters of municipalities with elevated dementia incidence. Spatial models are estimated both before and after adjustment for individual-level demographic and social health characteristics included in the balancing procedure. Comparing unadjusted and adjusted spatial patterns allows us to assess the extent to which geographic variation in dementia incidence reflects population composition in terms of observed demographic and social health characteristics. Clusters that attenuate after adjustment suggest compositional explanations, whereas those that persist point to potential contextual influences or unmeasured factors.

To further investigate contextual contributions, we extend the spatial scan statistics by incorporating municipality-level indicators of social infrastructure, including the density (per 10,000 inhabitants) of healthcare professionals, social workers, cultural venues, and retail stores. Population density is additionally included as a proxy for urbanicity, capturing differences in settlement structure that may shape service accessibility and opportunities for social interaction.

Our contribution is twofold. First, we extend the application of the MARMoT approach to a highly granular spatial setting, broadening its use beyond most previous applications. Second, we deepen the understanding of how the selected structural dimensions of social health, as operationalized in this study, relate to dementia risk in old age by examining their spatial distribution and persistence after covariate balancing and adjustment for area-level characteristics. Overall, our findings provide new evidence on the spatial structuring of social disadvantage and its implications for dementia risk in later life.

2. Data

2.1. Study population

The study population comprises all individuals born between 1935 and 1939 and residing in Finland in 2015, identified through the Finnish Population Register. These individuals were aged 76 to 80 in 2015 and were followed until 2019, reaching ages 79 to 84 during the observation period.

The analytical sample was further restricted to individuals living outside institutional care at baseline and with no recorded diagnosis or treatment for dementia prior to 2015, which serves as the baseline year. This restriction ensures that all participants were dementia-free and community-dwelling at study entry in 2015, thereby improving comparability in exposure to both individual and contextual social conditions.

The 1935-1939 cohort was selected to balance epidemiological relevance, measurement reliability, and internal validity. Dementia incidence increases sharply after age 75, whereas rates at younger ages are substantially lower and more heterogeneous. Focusing on individuals aged 75 and older allows for more stable estimation of spatial patterns at the municipal level and reduces noise related to the occurrence of early-onset dementia, which often follows distinct etiological pathways and clinical profiles and may be less sensitive to contextual and social conditions (Rossor et al., 2010).

At the same time, restricting the analysis to dementia-free individuals aged over 80 would generate a highly selected analytical population, thereby amplifying survival and health selection processes. The selected birth cohort (1935-1939) thus represents a compromise between capturing the age range at highest dementia risk and limiting excessive selection bias at very advanced ages.

Moreover, this cohort is the oldest for whom key structural and relational dimensions of social health, particularly intergenerational ties, can be measured with sufficient reliability in Finnish population registers. For earlier birth cohorts, incomplete fertility histories and parent-child linkages increase the risk of misclassification. This limitation has been acknowledged in previous register-based research and informed cohort definition in earlier studies (Einiö et al., 2016).

Finally, dementia diagnoses prior to 2015 are considered less reliable due to changes in diagnostic practices and data coverage over time. Initiating follow-up in 2015 enhances the consistency and comparability of case ascertainment across municipalities.

The study population was linked, using unique personal identification numbers, to national administrative datasets. These registers provide comprehensive longitudinal information on municipality of residence, health status, and key indicators of social health at both the individual and contextual levels.

2.2. Outcome

Dementia was ascertained using three complementary nationwide registers. First, the Care Register for Health Care (Finnish Institute for Health and Welfare), recording dementia diagnosis based on ICD-10 codes (F00–F03, G30, F05.1) and ICD-9 codes (290, 291.2, 331.0, 333.1, 437.8A, 294.1A, 298.8C) between 1996 and 2019. ICD-9 codes were used to identify dementia diagnosis between 1987 and 1995. Second, the Drug Reimbursement Register (Social Insurance Institution of Finland), which tracks purchases of dementia-related medications based on Anatomical Therapeutic Chemical (ATC) code N06D. Third, the Cause of Death Register (Statistics Finland), which records dementia as either the underlying or a contributing cause of death, using ICD-10 codes F01, F03, and G30.

Individuals were classified as having dementia from the date of their first recorded diagnosis or prescription of dementia-related medication. Once assigned, dementia status was considered irreversible for the remainder of follow-up.

For individuals with dementia recorded only at death and no prior diagnosis or medication use, dementia status was assigned starting two years prior to death. Without this procedure, such individuals would have remained classified as non-cases, leading to potential under-ascertainment.

Population-based evidence indicates that the median time from recorded dementia diagnosis to death is approximately five years (Joling et al., 2020). The two-year window was selected as a conservative operational assumption, acknowledging likely prior disease presence while limiting speculative backdating.

Dementia incidence was operationalized as cumulative incidence over the 2016-2019 follow-up period.

2.3. Operationalizing social health

We conceptualize social health as a multidimensional construct encompassing both individual vulnerabilities and contextual resources that shape opportunities for social engagement, autonomy, and support in later life. Drawing on prior research (e.g., Vernooij-Dassen et al., 2021), we operationalize social health using register-based indicators that capture relational and position-based social resources observable in administrative data. These indicators serve as structural proxies of social health. Although they do not directly measure perceived support or enacted participation, they capture durable social positions and relational configurations that condition access to support and social integration across the life course.

At the individual level, we include.

- Partnership status (currently co-residing with a partner);
- Parental status (having at least one registered biological or adopted child);
- Geographic proximity to children (having at least one child residing in the same municipality);
- History of widowhood (ever widowed during the life course);
- Disability status, derived from diagnostic categories recorded in administrative data that approximate long-term functional, intellectual, developmental, or sensory impairments (see Appendix A for ICD codes; Bister et al., 2025).

In line with our analytical strategy, these individual-level indicators are treated as confounders, namely characteristics that may influence both the exposure (the contextual environment of residence - municipality) and the outcome (dementia incidence). They are therefore included in the matching procedure to achieve covariate balance across municipalities. In addition, we adjust for two key socio-demographic characteristics: gender and educational attainment.

Educational attainment is included as a proxy for long-term socioeconomic status (SES) as a key determinant of cognitive reserve. As a stable early-life measure, education is less susceptible than income to reverse causation related to retirement or health decline. Moreover, evidence has shown that higher educational attainment is associated with more favourable cognitive trajectories and lower dementia risk, partly through its role in building cognitive reserve (Livingston et al., 2020; Meng and D'Arcy, 2012; Stern, 2012).

To examine the contribution of specific contextual factors, we include four area-level indicators reflecting local social infrastructure and service availability. These are measured as the density (per 10,000 residents) in 2015 of healthcare professionals, social workers, cultural venues (e.g., theatres, libraries, museums), and retail stores.

Healthcare and social worker indicators are derived from employment records, assigning workers to municipalities based on their workplace location. Cultural and retail indicators are based on the number of establishments in each municipality, as these venues may facilitate informal social interaction and community engagement. Together, these measures approximate the institutional and environmental capacity of local context to support social inclusion, interaction, and access to care in later life.

To account for broader structural differences across municipalities, we include population density (inhabitants per square kilometre). This measure captures variation in population concentration across municipalities, distinguishing more densely populated (typically urban) from more sparsely populated (typically rural) areas.

As a sensitivity analysis, we alternatively operationalized urbanisation using the degree of urbanisation, measured as the proportion of residents living in urban settlements within each municipality based on geocoded place-of-residence information. The results were substantively unchanged; therefore, population density was retained as the primary specification.

2.4. Contextual adjustment and aggregation

Population data from 2011 to 2018 served as the basis for computing per capita rates. These rates were calculated using denominators derived from the total municipal population, alongside sector-specific counts of employed individuals (in healthcare, social work, cultural, and retail sectors) and the number of establishments in the cultural and retail domains.

As of 2024, Finland comprises 308 municipalities with an average population size of 18,299 inhabitants. However, the distribution is highly skewed; while the median municipal population is 5,977, the smallest municipality is Lestijärvi (665 inhabitants) in mainland Finland and Sottunga (101 inhabitants) in the Åland Islands. At the other end of the spectrum, Helsinki is by far the most populous municipality, with 684,018 residents in 2025.

To enhance the reliability of area-level comparisons, we aggregated municipalities with very small older populations within our analytical cohort. Specifically, municipalities with fewer than 130 residents aged 76-80 (i.e. below the first quartile of the age-specific population distribution) were merged based on spatial adjacency and demographic similarity. These municipalities comprised 6,071 individuals in the target age group, representing only 3.3% of the total study population. Adjacency was defined using a contiguity matrix (i.e., shared borders), and merging was guided by minimizing multidimensional Euclidean distances based on municipality-level characteristics of the population such as the proportions of individuals living alone, childless, widowed, residing close to children, having experienced child's death, having low educational attainment, and living with a kin with disability. For geographically isolated areas (e.g., small islands, $n = 8$), aggregation was instead based on physical proximity only.

This procedure reduced the number of analytical units from 308 to 237, thereby improving the stability and robustness of contextual analyses. Overall, the aggregation involved a limited number of municipalities and affected a small proportion of the study cohort. Given its limited scope and the use of objective spatial and demographic criteria, the procedure is unlikely to introduce substantial aggregation bias while improving the reliability of area-level estimates. Additional details on the scope and magnitude of the aggregation procedure are provided in Appendix B.

3. Method

3.1. Matching on poset-based Average Rank for Multiple Treatments (MARMoT)

To identify clusters of municipalities in Finland where older adults are exposed to a higher risk of dementia, we applied the Matching on poset-based Average Rank for Multiple Treatments (MARMoT) approach, a non-parametric matching method designed to balance covariates across more than two groups in observational settings (Silan et al., 2021). MARMoT builds on the theory of partially ordered sets (poset), particularly on methods developed for estimating and approximating average ranks in such structures (Bruggemann and Carlsen, 2011; Caperna, 2019; De Loof et al., 2011). These methods allow for the derivation of a scalar summary of each individual's characteristics, the Average Rank (AR), which facilitates covariate balancing across multiple groups (i.e. Finnish municipalities) by generating a synthetic population in which the distribution of observed characteristics is similar across all geographic units.

By equalizing the composition of populations across municipalities, MARMoT allows for a credible interpretation of observed differences in dementia rates as reflecting contextual effects, rather than underlying compositional differences in individual-level risk factors.

The MARMoT procedure consists of the following steps.

1. Computation of the Average Rank (AR). Individual-level characteristics, both categorical and binary, are summarized into a single ordinal measure, the Average Rank (AR). This score reflects the degree to which each individual is exposed to characteristics potentially associated with dementia risk or selection into specific treatment groups.
2. Construction of a Frequency Table. A contingency matrix is generated, where rows represent distinct AR values and columns correspond to municipality. This table captures the distribution of individuals across municipalities by their AR value.
3. Definition of a Frequency Reference. For each AR level, a frequency reference is defined to serve as a benchmark across all municipalities. This ensures that municipalities are equally represented for each AR value, facilitating covariate balance.
4. Sampling to Create a Synthetic Balanced Population. Individuals are then randomly sampled within each municipality and AR level to match the frequency reference. This results in a synthetic population where the distribution of individual characteristics is balanced across municipalities.

The procedure is implemented using the R package *MARMoT* (Calore et al., 2024), which provides tools for computing average ranks and generating the synthetic balanced dataset.

The MARMoT approach offers several advantages for this study. First, it enables balancing across a large number of groups (i.e., municipalities), without imposing parametric assumptions about treatment assignment. Second, it accommodates categorical and binary covariates in a principled and non-parametric manner. Third, it produces a synthetic population in which the distribution of observed characteristics is balanced across groups, thereby strengthening the credibility of inferences regarding contextual effects.

The goal of the method is to achieve comparability between groups with respect to observed confounders (i.e., demographic and social health characteristics), supporting the conditional independence (unconfoundedness) assumption required for causal inference. It constructs a synthetic sample in which the distribution of observed covariates is balanced across multiple treatment groups. To assess the effectiveness of the matching procedure, we compute the Absolute Standardized Bias (ASB) for each covariate using the following formula:

$$ABS = \frac{|\overline{X}_t - \overline{X}|}{\sqrt{\frac{s_t^2 + s^2}{2}}} * 100$$

where $\overline{X}_t$ and $\overline{X}$ denote the mean of covariate in the treatment group and the overall sample, respectively, and s_t^2 and s^2 are the corresponding variances.

An ASB value below 10% is commonly considered indicative of acceptable balance in the matching literature (Austin, 2009; Stuart, 2010; Rosenbaum and Rubin, 1985). However, this threshold should be interpreted in relation to the importance of the confounding variable in the prediction of the outcome. This diagnostic provides an assessment of the extent to which the matching procedure has reduced covariate imbalance prior to the analysis of contextual effects.

3.2. Detection of high-risk dementia clusters using spatial scan statistics

After balancing individual-level characteristics across municipalities using the MARMoT procedure, we first identified spatial clusters where dementia incidence remained significantly elevated. This step allows us to assess whether geographic disparities persist after accounting for observed demographic and structural social health characteristics at the individual level. In a second step, we incorporated area-level indicators of social infrastructure into the model to examine whether these contextual factors further attenuate or modify the detected clusters.

To this end, we applied spatial scan statistics (SSS), a class of methods designed to identify clusters of adjacent areas with significantly elevated or reduced risk of an outcome. SSS systematically scans the study area using moving windows, testing whether the incidence of dementia within each window significantly differs from that outside it (Kulldorff, 1999; Naus, 1965). The output consists of one or more statistically significant clusters, representing areas where observed incidence within the cluster exceeds that outside the cluster under the specified model.

In this study, we employ a model-based scan statistic implemented in the R package *DClusterm* (Gómez-Rubio et al., 2019), which builds on generalized linear models to identify spatial clusters. The method uses a series of dummy variables and performs likelihood ratio tests to compare nested models with and without the candidate cluster term. Previous studies have demonstrated how this method can be applied in different scenarios (Bovo et al., 2025; Silan et al., 2023).

We first estimate a baseline Poisson regression model (null model), where the number of observed dementia cases per area is the dependent variable, and the number of individuals at risk is included as an offset term. This specification yields area-level dementia incidence rates. Individual-level demographic and social health characteristics, together with area-level covariates, were included to account for potential confounding in the estimation of incidence rates.

Once the baseline model is fitted, the algorithm searches for spatial clusters by selecting a centroid (i.e., a starting area) and progressively adding neighbouring areas one by one. At each iteration, a new model is estimated that includes a binary term indicating whether an area belongs to the candidate cluster. A likelihood ratio test compares this extended model to the baseline. If the added area improves the model fit by indicating a significantly higher dementia incidence, it is retained in the cluster. The process continues until no further improvement is observed or no more neighbouring areas are available.

The algorithm can be customized using stopping rules, for example by setting thresholds on the maximum number of areas or total population allowed in a cluster. In this study, no population constraints were imposed during the spatial scan.

For each finalized cluster, *DClusterm* computes an approximate p-value based on a chi-squared distribution with one degree of freedom. Since no prior assumptions were made regarding the potential location of clusters, the algorithm was run from each area as a potential centroid. The final output includes only those clusters whose p-values fall below a pre-specified significance level, set at 0.10.

4. Results

4.1. Individual-level social health covariate balance and dementia incidence

To evaluate the effectiveness of the MARMoT procedure in balancing individual-level covariates across municipalities, we computed the Absolute Standardized Bias (ASB) for each variable, both on real data and on balanced data. Table 1 summarizes the distribution of ASB values across all covariates and areas, while Fig. 2 illustrates the mean ASB per covariate before and after matching.

The results indicate an overall improvement in covariate balance following adjustment. In the unadjusted data, the median ASB was 7.3%, and the mean ASB 9.7%, suggesting notable heterogeneity in the distribution of individual-level characteristics across municipalities. Extreme imbalance was observed in some municipalities, with the maximum ASB reaching 95.8%.

After MARMoT adjustment, the median ASB decreased to 5.2%, and the mean to 6.6%, indicating a substantial improvement in balance across municipalities (Table 1). Although the maximum ASB remained high (52.8%), such extreme values were confined to a small number of outlying municipalities. The proportion of municipalities exhibiting substantial imbalance declined markedly after adjustment: the number with ASB >20% decreased from 198 to 55, those with ASB >10% fell from 621 to 379, and those with ASB >5% from 1,074 to 840. Residual imbalance was primarily concentrated in smaller municipalities, where limited population size makes it more challenging to identify suitable matches and achieve full balance across covariates.

As illustrated in Fig. 1, most covariates experienced notable reductions in mean ASB following balancing. Education attainment and municipality-level proximity to children were among the most imbalanced variables prior to matching and showed substantial reductions after adjustment. Even variables that were already relatively balanced, such as gender, partnership status, and widowhood, showed further improved comparability across municipalities. Despite these improvements, education and disability remained the most imbalanced covariates post-adjustment, with a non-negligible number of municipalities still exceeding conventional balance thresholds. These residual differences should be interpreted considering the substantial pre-matching disparities and the methodological challenge of achieving simultaneous balance across 237 municipalities, rather than within a binary treatment framework.

Improvements were also observed for variables not directly included in the balancing procedure. For example, the ASB for being divorced decreased from 11.5% to 8.4%, and for living alone from 8.1% to 7.3%, suggesting that the MARMoT procedure may also contribute to broader stabilization of related covariate distributions.

Overall, the observed reductions in ASB indicate a meaningful improvement in comparability across municipalities with respect to measured covariates, while acknowledging the persistence of some residual imbalance.

As shown in Fig. 2, dementia incidence varied markedly across municipalities before adjustment for individual-level covariates (left panel), while the adjusted distribution (right panel) appears more homogeneous, suggesting that a substantial share of the variation observed in the unadjusted data is consistent with compositional differences in socio-demographic and social health characteristics.

After adjustment, only a limited number of municipalities remain at the upper end of the observed dementia incidence distribution (Fig. 2, right panel). The post-balancing incidence can be interpreted as the dementia incidence that would be expected if municipalities shared a comparable individual-level risk profile with respect to the selected socio-demographic and social health characteristics. Accordingly, the reduction in overall dementia incidence and spatial heterogeneity

Table 1
Distribution of Absolute Standardized Bias (ASB) across municipalities, before and after MARMoT adjustment.

ASB	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Over 5%	Over 10%	Over 20%
Before	0.007	3.437	7.344	9.673	13.519	95.766	1,074	621	198
After	0.074	2.348	5.176	6.602	9.426	52.799	840	379	55

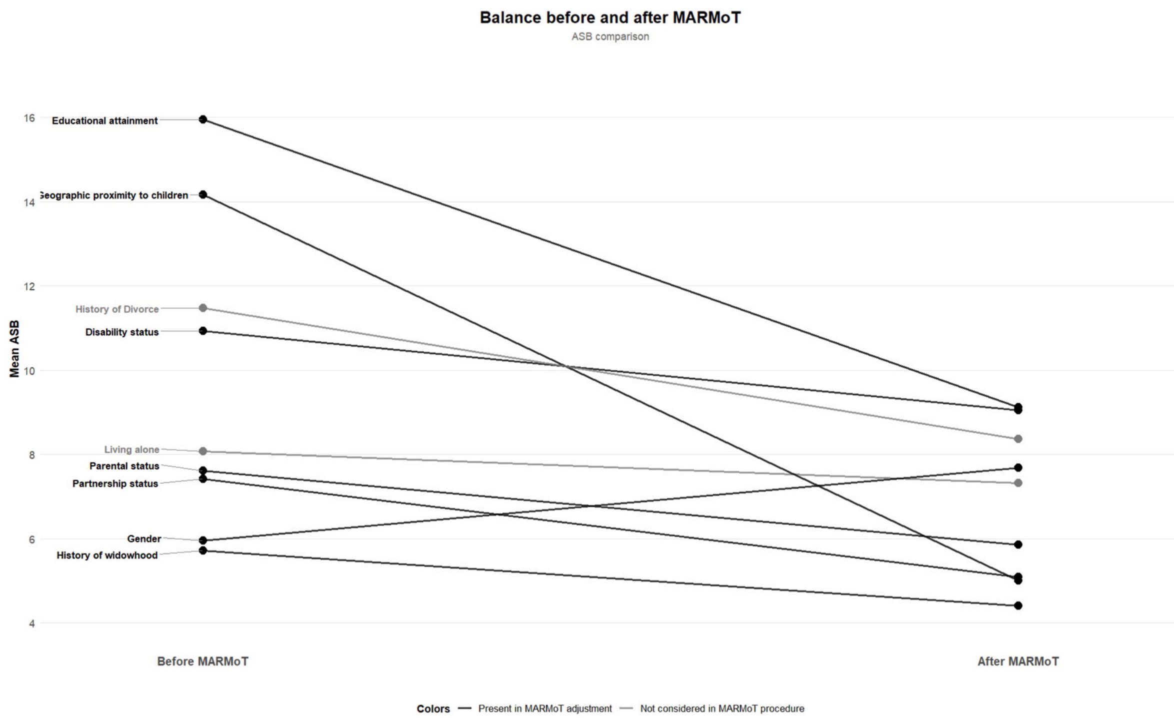

Fig. 1. Mean Absolute Standardized Bias (ASB) by covariate, before and after MARMoT adjustment.

provides descriptive evidence of the extent to which observed geographic disparities are associated with inequalities in individual-level demographic and structural social health resources. Under the assumption of unconfoundedness, any remaining differences in dementia incidence across municipalities after MARMoT adjustment are consistent with a combination of contextual conditions and unmeasured individual or life-course factors. Although the matching procedure substantially reduces observed compositional heterogeneity, residual spatial variation should not be interpreted as purely contextual.

4.2. Spatial clustering of dementia incidence before and after adjustment

We applied spatial scan statistics to identify contiguous clusters of municipalities with elevated dementia incidence, first in the unadjusted data and subsequently after balancing individual-level demographic and structural social health characteristics. Comparing these models allows us to assess whether high-risk clusters are primarily associated with population composition or whether excess incidence persists after accounting for observed individual-level differences.

In the unadjusted model (Fig. 3, left panel), six statistically significant spatial clusters of high dementia incidence were identified. The largest cluster was located in the east-central region of the country and included several neighbouring municipalities with an excess risk of 0.17, indicating that incidence within the cluster was, on average, 17% higher than the remainder of the territory. Additional clusters were observed in southern Finland, including the Helsinki metropolitan area, as well as in southwestern and west-central regions, with excess risk ranging from 0.06 to 0.36.

After MARMoT adjustment (Fig. 3, right panel), the spatial pattern changed. Four statistically significant clusters were identified, with excess risks ranging from 0.21 to 0.51. The large east-central cluster persisted, although its geographic extent was reduced. This attenuation suggests that part of the excess incidence in this region was associated with compositional differences in socio-demographic and structural social health characteristics, while a residual excess remained after balancing observed individual-level factors.

In addition, a new west-central cluster emerged only after adjustment. This indicates that excess dementia incidence in this area became detectable once differences in measured population composition were accounted for, suggesting that compositional heterogeneity had previously obscured this pattern.

In a further step, we incorporated area-level indicators of social infrastructure (density of healthcare professionals, social workers, cultural venues, retail stores) and population density into the model. The inclusion of these contextual variables did not materially alter the clustering results. The persistence of residual clusters after accounting for both individual-level composition and measured contextual characteristics suggests that the remaining spatial variation is not fully explained by the observed factors considered in the analysis.

5. Discussion and conclusion

This study examines how individual socio-demographic and social health resources, together with contextual conditions, shape geographic variation in dementia incidence in Finland. By combining covariate balancing with spatial scan statistics, we advance understanding of how compositional and contextual factors interact in structuring dementia risk in ageing societies.

Using the MARMoT procedure to balance municipalities on individual-level demographic and structural social health

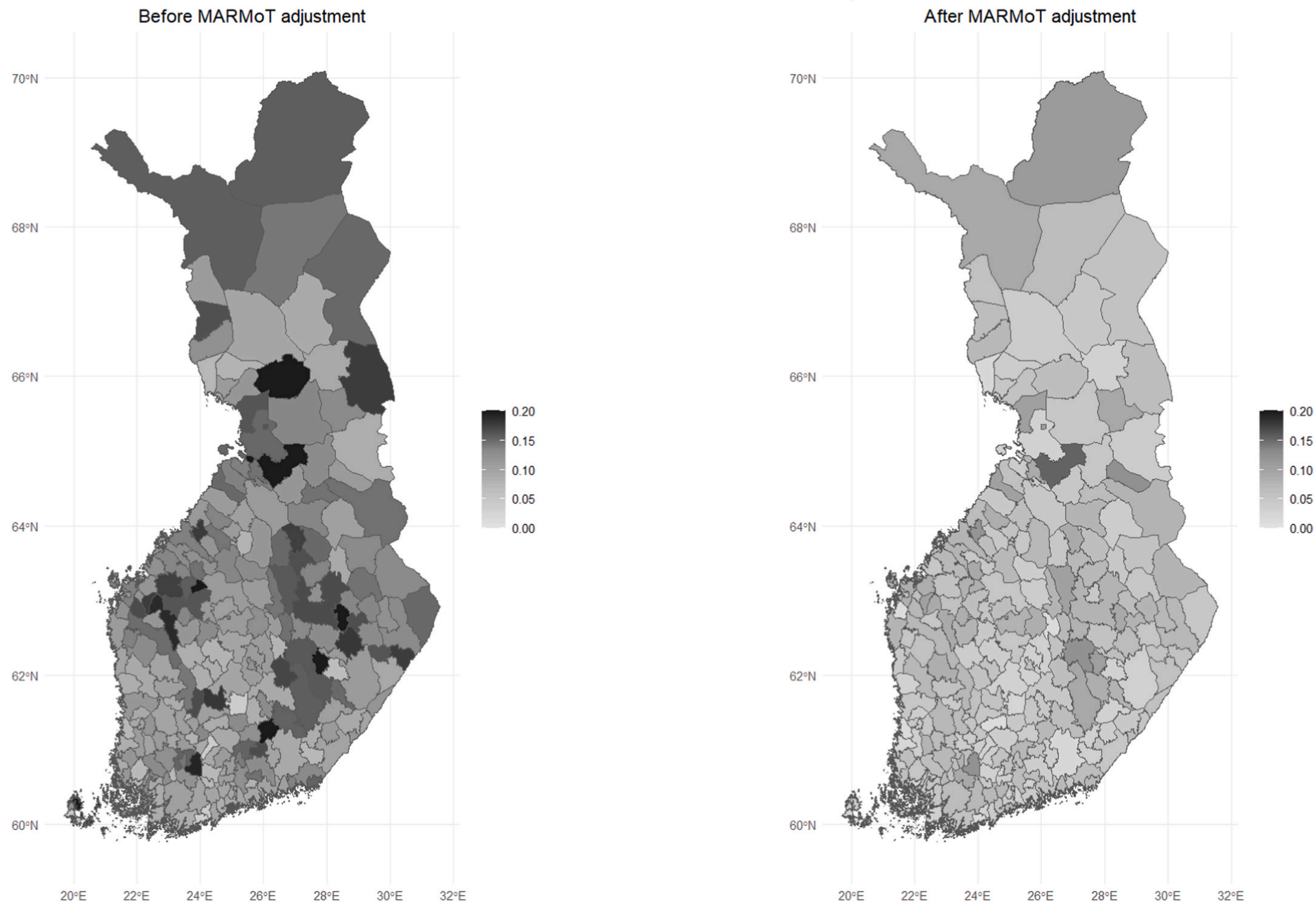

Fig. 2. Municipality-level dementia incidence before (left) and after (right) MARMoT adjustment.

characteristics, we assessed the extent to which observed spatial disparities reflect differences in population composition. In several areas, including the Helsinki metropolitan region, elevated dementia incidence observed in the unadjusted model largely attenuated after adjustment. This suggests that excess risk in these areas was primarily associated with the concentration of socio-demographically disadvantaged or socially vulnerable groups.

In contrast, in parts of eastern Finland, excess dementia incidence persisted after balancing individual-level characteristics. This residual geographic variation indicates that incidence remains higher than expected given measured socio-demographic composition and structural social health indicators. While the underlying mechanisms cannot be identified with the available data, the persistence of excess risk suggests that observed disparities are not fully captured by the measured characteristics.

A west-central cluster emerged only after adjusting for population composition. This pattern indicates that favourable socio-demographic and social health profiles had previously masked elevated incidence in this area. Once compositional differences were accounted for, excess risk became detectable, underscoring the importance of explicitly addressing population heterogeneity in spatial analyses.

When area-level indicators of social infrastructure and population density were incorporated into the model, clustering patterns did not materially change. In this context, geographic variation in dementia incidence appears more strongly associated with compositional differences across municipalities than with the contextual indicators measured in this study. However, these findings should be interpreted with caution, as it may partly reflect limitations in the granularity or specificity of the available area-level measures, for example, the inability to capture service quality, accessibility, or user experience.

Methodologically, this study demonstrates the value of combining matching-based balancing with spatial cluster detection. Traditional regression adjustment controls for confounders parametrically but does not directly equalize their distribution across geographic units. By contrast, MARMoT generates a synthetic population balanced on key covariates prior to spatial analysis, thereby reducing systematic compositional heterogeneity and facilitating clearer interpretation of residual spatial variation. Moreover, the use of spatial scan statistics enables the detection of contiguous clusters rather than isolated excess-risk units, providing insights that are potentially more informative for public health monitoring and territorial policy planning. At the same time, residual clustering remains conditional on the set of observed covariates and does not imply the identification of “pure” contextual effects.

One key implication of this study is that spatial disparities in dementia incidence may arise from distinct underlying mechanisms, requiring differentiated policy responses. Effective dementia prevention strategies therefore require integrated approaches that combine population-level efforts to strengthen social health with place-sensitive interventions tailored to local service environments and territorial constraints.

In areas where excess dementia risk largely attenuates after balancing individual-level socio-demographic and structural social health characteristics, elevated incidence appears primarily associated with the concentration of socially vulnerable populations. In such contexts, prevention efforts may benefit from strengthening structural social

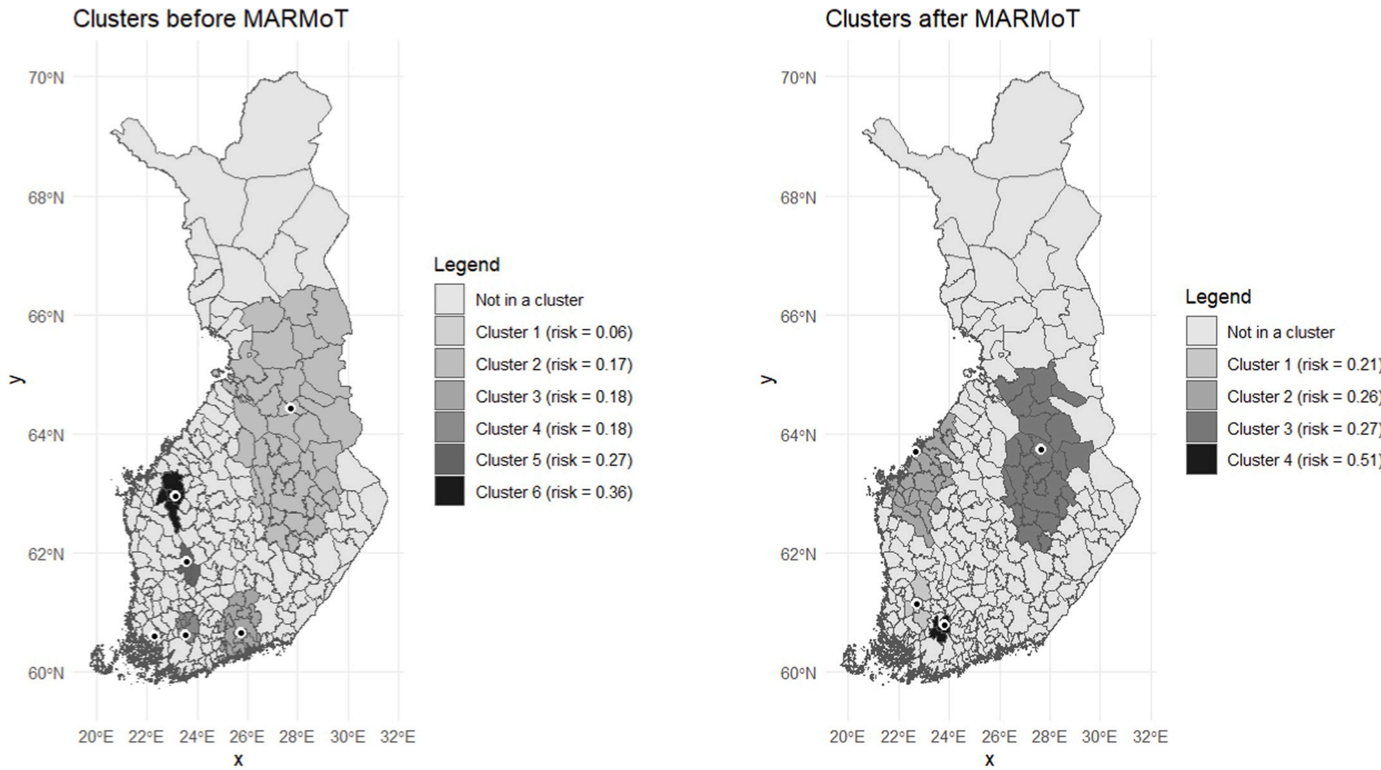

Fig. 3. Spatial clusters of high dementia incidence before MARMoT (left) and after (right) adjustment.

health resources at the population level. Examples include initiatives that promote social connectedness among older adults living alone or widowed, community-based programs that facilitate intergenerational contact, outreach services targeting socially isolated individuals, and local coordination between primary care and social services to identify at-risk groups. Policies aimed at reducing social vulnerability, such as improving access to social support networks, facilitating mobility, and supporting informal caregiving structures, may indirectly contribute to cognitive health by enhancing opportunities for engagement and support in later life.

By contrast, in areas where excess dementia incidence persists or becomes more apparent after balancing population composition, spatial variation is less readily attributable to observed individual-level characteristics. In these settings, attention may need to focus more explicitly on contextual and institutional dimensions. For example, variation in diagnostic practices, referral pathways, service coordination, and case recording may influence observed incidence. Strengthening early detection mechanisms, harmonizing diagnostic criteria, improving access to memory clinics, or addressing geographic barriers to care, particularly in sparsely populated or remote municipalities, may represent relevant policy levers.

Persistent clustering may also reflect unmeasured contextual exposures, such as differences in environmental risk factors, long-term occupational structures, or historically accumulated socio-economic disadvantage. While these mechanisms cannot be directly assessed with the available data, their plausibility underscores the importance of integrating environmental monitoring, life-course data, and institutional analyses into future research and policy planning.

Although our area-level indicators did not materially alter clustering patterns, this should not be interpreted as evidence that local context is irrelevant. Rather, it may reflect the limited specificity or granularity of available measures. The quality, accessibility, and coordination of services, as well as everyday environmental features that facilitate participation and social interaction, are not fully captured by counts of infrastructure. Ensuring equitable access to culturally and geographically appropriate services remains central to dementia prevention and care.

This study has several limitations. Although the Finnish population registers provide rich and high-quality nationwide data, our operationalization of social health was constrained to structural and relational dimensions observable in administrative sources. Subjective and behavioural components, such as loneliness, social participation trajectories, or informal caregiving dynamics, could not be directly captured. The selection of indicators reflects a deliberate focus on a minimum viable set of durable structural and relational positions that can be reliably measured in population registers. Rather than attempting to operationalize social health as a latent multidimensional construct, we prioritize observable confounders suitable for covariate balancing within a spatial comparative framework. Additional candidate variables available in the registers (e.g., living alone, divorce history) were explored but showed substantial overlap with the retained indicators. For reasons of parsimony, interpretability, and model stability in a matching-based design across a large number of municipalities, the final specification was therefore restricted to the selected variables.

Similarly, the available area-level indicators do not fully capture environmental exposures, institutional practices, or differences in service quality and accessibility. Residual spatial clustering should therefore be interpreted as identifying areas where observed incidence exceeds expectations based on measured characteristics, rather than as definitive evidence of contextual causation. Such clustering may reflect a combination of unmeasured life-course processes, contextual influences, and diagnostic or service-related factors. Future research integrating environmental, institutional, biological, and longitudinal life-course data would help clarify the mechanisms underlying spatial disparities in dementia incidence and improve the interpretability of spatial health inequalities.

Finally, the analysis was restricted to individuals born between 1935 and 1939. While this cohort ensures reliable linkage of intergenerational ties and stable incidence estimation at older ages, findings are most informative for cohorts currently in advanced older age. Patterns of life-course exposure to healthcare systems, diagnostic practices, and social policies may differ for younger generations, limiting the direct applicability of these findings to future ageing cohorts.

In terms of cross-national comparability, although Finland has specific institutional and administrative features, its socio-demographic structure and welfare regime share important similarities with other Nordic and European contexts characterized by universalistic welfare arrangements and advanced population ageing. While caution is warranted in generalizing results beyond the Finnish case, the analytical framework and observed patterns may offer insights relevant to countries with comparable demographic and institutional settings.

To our knowledge, this is the first study to operationalize structural dimensions of social health using nationwide register data within a spatial analytical framework. Despite the inherent constraints of administrative sources, our findings demonstrate the potential of combining administrative data with balancing and spatial methods, offering a replicable strategy for investigating social and geographic inequalities in dementia outcomes.

Ethical_declaration

The Statistics Finland Board of Ethics and the Social and Health Data Permit Authority Findata approved the study (permit numbers TK/1529/07.03.00/2025 for StatFin and THL/5298/14.06.00/2025 for Findata), and the data were pseudonymized before being provided to the researchers.

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

During the preparation of this work, the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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CRediT authorship contribution statement

Elisa Cisotto: Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Margherita Moretti:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – review & editing. **Margherita Silan:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – review & editing. **Joan Damiens:** Data curation, Formal analysis, Methodology, Software, Validation, Writing – review & editing. **Pietro Belloni:** Formal analysis, Methodology, Software, Visualization, Writing – review & editing. **Kaarina Korhonen:** Conceptualization, Writing – review & editing. **Pekka Martikainen:** Data curation, Funding acquisition, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no conflicts of interest.

APPENDIX A. Diagnostic Codes Used to Identify Disability

Data for measuring disability were drawn from the Finnish population registers maintained by Statistics Finland (StatFi), the Finnish Institute for Health and Welfare (THL), and the Social Insurance Institution of Finland (Kela). Specifically, diagnostic information was obtained from the following register sources: the Care Register for Health Care, the Register for Congenital Malformations, and the Register for the Reimbursement of Private Health Care Costs.

To comprehensively capture individuals' long-term functional limitations, we identified relevant diagnoses using both ICD-10 and ICD-9 codes. This dual coding approach enables the inclusion of diagnoses made prior to the adoption of ICD-10 in Finland, thereby extending coverage back to 1987. The binary indicator for lifetime disability status was constructed based on the presence of at least one of the following conditions.

ICD-10 codes.

- F70–F79 (mental retardation),
- Q90–Q99 (chromosome abnormalities),
- G80–G83 (cerebral palsy and other paralytic syndromes),
- Q86–Q89 (other congenital - physical - malformations),
- R26 (abnormalities of gait and mobility),
- H54 (severe visual impairment and blindness),
- H90 (conductive and sensorineural hearing loss),
- F84 (pervasive developmental disorders).
- ICD-9 codes:
– 317–319 (intellectual disabilities),
– 333 (extrapyramidal and movement disorders),
– 343 (infantile cerebral palsy),
– 758 (chromosomal anomalies),
– 781.2 (abnormal gait),

– 369 (visual impairment),
– 389 (hearing loss),
– 299 (pervasive developmental disorders).

APPENDIX B

Aggregation of Municipalities and Impact on Analytic Units

Indicator	Value
Total number of municipalities before aggregation	308
Municipalities below aggregation threshold	76
Aggregation threshold	<130 individuals aged 76-80 (1st quartile)
Resulting spatial units after aggregation	237
Total number of individuals in all municipalities	185,712
Individuals affected by aggregation (N)	6,701
Individuals affected by aggregation (%)	3.3%
Aggregation criterion	Spatial adjacency and demographic similarity
Maximum number of municipalities merged into one unit	9 (*single island-based unit; all other units* ≤*4*)
Median number of municipalities merged per unit	2
Number of isolated island municipalities aggregated	7 (Åland and Turku archipelago)

Note: Aggregation was applied exclusively to municipalities with very small older populations to improve statistical stability in area-level analyses. A total of 76 municipalities were aggregated, corresponding to 6,701 individuals (3.3% of the study cohort). Municipalities were merged based on spatial adjacency and demographic similarity, increasing the number of individuals and dementia cases per spatial unit while preserving geographic comparability across units. The maximum aggregation of nine municipalities refers to a single spatial unit in the Turku archipelago composed of geographically isolated island municipalities; excluding this case, the maximum number of municipalities merged into one unit was four.

Data availability

The authors do not have permission to share data.

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