Linking provider catchment patterns and SaTScan risk clusters to support evidence-based public health nursing in urban Japan

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Abstract

Municipal public health nurses require geographic evidence to identify concentrated health risks and understand where residents access preventive services. This study describes a reproducible workflow combining provider catchment analysis and spatial scan statistics using Japan's Specific Health Checkups data from a single local government area in Japan. The protocol was approved by the institutional ethics review board (approval number 2024-053). Service use patterns were summarized across seven elementary school districts. Elevated glycated hemoglobin, defined as HbA1c ≥ 5.6%, was assessed at the chome level, using neighborhood scale address units. QGIS was used for spatial processing, R for statistical analysis, and SaTScan for Poisson spatial scan statistics. Residential district and provider location category were strongly associated ($p < 0.01$). Within district use ranged from 6.8% to 72.5%, out of area use from 11.2% to 37.3%, and group screening from 3.8% to 7.1%. The most likely high risk cluster included 9,577 adults, with 400 observed and 315.80 expected cases (observed/expected = 1.27; RR = 1.37; $p < 0.01$). Two secondary high risk clusters were detected but were not statistically significant. Linking catchment patterns with chome level risk clusters supports interpretation of local prevention needs and service use. The use of census based population denominators rather than chome specific participant counts may influence cluster detection. This reproducible workflow provides a transparent and adaptable basis for local public health planning.

1. Introduction

Public health nursing practice requires an understanding of both population needs and the local systems through which preventive services are delivered. Municipal public health nurses use routinely collected data to characterize community health needs, plan outreach activities, communicate health risks, and coordinate prevention strategies with clinical providers. However, statistics aggregated for an entire local government area may conceal substantial variation among smaller geographic units. Local planning therefore requires evidence regarding not only where health risks are concentrated, but also where residents access preventive services.

Japan's Specific Health Checkups program provides an important data source for this purpose. Introduced in fiscal year 2008, the program targets insured adults aged 40–74 years and focuses on the prevention and improvement of metabolic syndrome. Specific health guidance is provided to eligible individuals according to their checkup results (Ministry of Health, Labour and Welfare, 2024). The accumulated records include clinical measurements and questionnaire items relevant to chronic disease prevention. When analyzed at geographic scales corresponding to local practice, these routinely collected data can support more detailed assessment of population needs and preventive service use.

Previous studies have demonstrated the value of geographic analysis using health checkup data in Japan. Nagakura et al. (2021) examined associations between health examination results and population health indicators across prefectures using a nationwide health checkup database. Okui and Park (2022) analyzed differences in hypertension and related risk factors according to deprivation at the area level across secondary medical areas. Suzuki et al. (2019) visualized geographic variation in factors associated with willingness to improve lifestyle behaviors using Specific Health Checkups data from a local government area. These studies indicate that the distribution of health risks and related behaviors varies across geographic settings.

Related studies have examined the geographic dimensions of preventive service use and metabolic risk. Fujita et al. (2017) reported that geographic accessibility and income level were associated with utilization of annual health checkups. Fukuoka et al. (2021) used geographic information system methods to examine associations between the inconvenience of residential location and individual HbA1c levels in a rural area. Mizutani et al. (2024) applied spatial cluster analysis and spatial regression to identify prefectural clusters with high participation rates in Specific Health Checkups and to examine associated regional factors. These findings demonstrate that preventive service use, health risks, and the environments in which residents live are geographically structured.

An operational gap nevertheless remains. Analyses of health risk concentration and analyses of preventive service utilization are commonly conducted separately. A map of elevated risk can identify areas where prevention needs are concentrated, but it does not necessarily indicate the providers or service channels through which residents in those areas can be reached. Conversely, an analysis of provider use patterns can identify where residents receive preventive services, but it does not determine whether the populations using those providers include residents from areas with statistically significant concentrations of health risk. Administrative boundaries alone may therefore provide an incomplete basis for planning outreach and provider collaboration.

Spatial scan statistics offer a method for detecting geographic concentrations of health outcomes without requiring the location or size of a potential cluster to be specified in advance (Kulldorff, 1997). Provider catchment analysis provides a complementary perspective by summarizing observed relationships between residential areas and provider locations. Linking the outputs of these analyses can connect need, represented by small area risk concentration, with reach, represented by actual patterns of preventive service utilization. This linkage is relevant to public health nursing because the geographic distribution of residents with elevated risk may not correspond directly to the locations of the providers they use.

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This study describes and applies a reproducible geospatial workflow that combines provider catchment analysis and spatial scan statistics using records from Japan's Specific Health Checkups program in a single local government area in Japan. The analysis addresses two questions: (1) how preventive checkup utilization differs across residential districts and (2) whether elevated glycated hemoglobin, defined as HbA1c ≥ 5.6%, is geographically concentrated at the chome level. Rather than proposing a single integrated statistical model, the workflow links the outputs of complementary analyses within a shared geographic framework. The purpose is to provide interpretable evidence that can support local outreach planning, communication strategies, and collaboration between public health nurses and clinical providers.

2. Materials and Methods

2.1 Study Setting and Analytical Framework

This study was conducted in a single local government area in Japan using records from Japan's Specific Health Checkups program for adults aged 40–74 years. A cross sectional geospatial framework was developed to examine two complementary dimensions of local preventive health practice: the geographic structure of service utilization and the spatial concentration of elevated diabetes risk.

The analysis was conducted at two spatial scales. First, provider catchment patterns were summarized using seven elementary school districts as residential origin units. These districts were used because they provide locally interpretable geographic units for examining where residents received preventive checkups. Second, spatial clustering of elevated glycated hemoglobin was assessed at the chome level. Chome are neighborhood scale address units in Japan and provide a finer spatial resolution for identifying localized concentrations of risk.

The analytical framework consisted of two linked components. The first component quantified the association between residential district and provider location category using an origin destination table. The second component identified statistically significant chome level clusters of elevated HbA1c using spatial scan statistics. These components were interpreted within a shared geographic framework rather than combined into a single statistical model. The purpose of this linkage was to support interpretation of where elevated risk was concentrated and which preventive service pathways were most relevant to residents of the study area.

2.2 Specific Health Checkup Data

The analysis used records from Japan's Specific Health Checkups program collected in the study area between April 2022 and March 2023. The program targets insured adults aged 40–74 years and is intended to support the prevention and improvement of metabolic syndrome. The eligibility criteria for the present study required non-missing data for both HbA1c and the provider institution at which the checkup was received. All 3,200 participants met these criteria. No records were excluded, and all available records were included in the analysis.

The variables used in the present analysis were residential elementary school district, residential chome, provider location category, and glycated hemoglobin level. Residential information was used only to assign each record to the relevant geographic unit. Provider location was classified into nine categories: seven elementary school districts within the study area, providers outside the study area, and group screening. The primary outcome for the spatial cluster analysis was elevated HbA1c, defined as HbA1c ≥ 5.6%, as an indicator of increased diabetes risk.

No individual locations were mapped or reported. Provider catchment patterns were analyzed using aggregated origin destination counts at the elementary school district level. Spatial cluster analysis was conducted using aggregated chome level case counts linked to polygon centroids.

2.3 Spatial Units of Analysis

Two geographic units were used according to the analytical purpose. Provider catchment patterns were analyzed using seven elementary school districts within the study area. Each participant was assigned to a residential school district, which served as the origin unit in the analysis. Provider locations within the study area were classified using the same seven school districts, allowing service utilization within and across residential districts to be summarized consistently.

Spatial clustering of elevated HbA1c was assessed using chome units. Chome are neighborhood scale address units in Japan and provide a finer geographic resolution than elementary school districts. Each chome polygon was assigned a unique location identifier. Polygon centroids were derived and used as the geographic coordinates for the spatial scan analysis.

Boundary data for the elementary school district and chome units were obtained from e-Stat, the Portal Site of Official Statistics of Japan. Population denominators for residents aged 40–74 years were also obtained from e-Stat. These denominators were linked to the corresponding chome units for the Poisson spatial scan analysis (e-Stat, 2026).

2.4 Provider Catchment Analysis

Provider catchment patterns were examined using an origin destination contingency table by R (R Core Team, 2026). The rows represented the seven residential elementary school districts, and the columns represented nine provider location categories: the seven elementary school districts within the study area, providers outside the study area, and group screening. The table therefore summarized where residents of each district received their Specific Health Checkups.

2.4.1 Origin Destination Contingency Table: For each residential district, the number of participants using each provider location category was tabulated. Provider locations within the study area were classified according to the elementary school district in which the provider was located. Providers located outside the study area were combined into a single out of area category. Group screening was treated as a separate service channel.

The association between residential district and provider location category was evaluated using Pearson's chi square test. The null hypothesis was that provider location category was independent of residential district.

2.4.2 Standardized Residual Analysis: Standardized residuals were examined for each cell of the contingency table to characterize the structure of the observed association. Positive residuals indicated that an origin destination pair was used more often than expected under independence, whereas negative residuals indicated lower than expected utilization. Particular attention was given to within district cells, which represented the use of providers located in the same elementary school district as the participant's residence.

2.4.3 District Specific Catchment Indicators: Three district specific indicators were calculated for each residential district:

within district use, out of area use, and group screening use. Within district use was defined as the proportion of participants who received checkups from providers located in their residential district. Out of area use was defined as the proportion who used providers outside the study area. Group screening use was defined as the proportion who received checkups through group screening. These indicators were used to describe heterogeneity in service utilization patterns across the seven residential districts.

2.5 Spatial Scan Analysis of Elevated HbA1c

2.5.1 Outcome and Population Denominator: The outcome for the spatial cluster analysis was elevated glycated hemoglobin, defined as HbA1c $\geq$ 5.6%. For each chome unit, the number of Specific Health Checkups participants meeting this criterion was aggregated as the case count. The population denominator was the number of residents aged 40–74 years in the corresponding chome unit, obtained from e-Stat (e-Stat, 2026). The denominator represented the census based population rather than the number of Specific Health Checkups participants.

2.5.2 Preparation of SaTScan Input Data: Spatial data processing was performed in QGIS (QGIS.org, 2026). Each chome polygon was assigned a unique location identifier, and its centroid coordinates were derived. Three input datasets were prepared for the spatial scan analysis: (1) chome level case counts for participants with HbA1c $\geq$ 5.6%, (2) chome level population denominators for residents aged 40–74 years, and (3) centroid coordinates linked to the corresponding location identifiers. No individual residential locations were entered into the spatial scan analysis.

2.5.3 Poisson Spatial Scan Statistic: A purely spatial scan analysis was conducted using SaTScan version 10.1, 64 bits. SaTScan is open-source software for the analysis of spatial, temporal, and space-time clusters (Kulldorff, 2022; SaTScan, 2026). The discrete Poisson probability model was applied because aggregated case counts and population denominators were available for each chome unit (Kulldorff, 1997). Under the null hypothesis, the expected number of cases in each chome unit was proportional to its population aged 40–74 years.
Following the settings used by Horiike et al. (2024), circular scanning windows were applied, and the maximum spatial cluster size was set to 50% of the population at risk. Statistical significance was evaluated using 999 Monte Carlo permutations. Secondary clusters were reported only when they had no geographical overlap. The threshold for statistical significance was set at $p < 0.05$.
The analysis reported the population within each detected cluster, observed and expected case counts, observed to expected ratios, relative risks, and p values. High risk clusters were reported in the main analysis.

2.6 Ethical Considerations

The study protocol was approved by the institutional ethics review board of the author's university (approval number 2024-053).

3. Results

3.1 Analytical Sample

The dataset contained 3,200 records from Japan's Specific Health Checkups program collected between April 2022 and March 2023. Records were eligible for inclusion when data were available for both HbA1c and the provider institution at which the checkup was received. All 3,200 records met the eligibility criteria, and no records were excluded. Among the participants included in the analysis, 1,482 (46.3%) had elevated HbA1c, defined as HbA1c $\geq$ 5.6%.

3.2 Provider Catchment Patterns

Table 1 presents the distribution of provider location categories according to residential elementary school district. The number of participants varied across the seven residential districts, ranging from 227 in District G to 814 in District B. The proportion of participants using providers located within their residential district ranged from 6.8% in District C to 72.5% in District A. Out of area utilization ranged from 11.2% in District A to 37.3% in District E, while group screening accounted for 3.8% to 7.1% of checkups across the seven districts.
The most frequently used provider location category differed among residential districts. Participants residing in Districts A, D, and F most frequently used providers located within their residential districts. Participants residing in Districts B and E most frequently used providers located outside the study area. Participants residing in District C most frequently used providers located in District A, whereas participants residing in District G most frequently used providers located in District D.
Residential district and provider location category were significantly associated (Pearson's $\chi^2 = 2864.8$, df = 48, $p < 0.01$). Table 2 presents the adjusted standardized residuals for each origin destination pair. Positive residuals were observed for all seven within district cells, ranging from 10.48 to 25.05, indicating higher utilization than expected under independence. Additional positive residuals greater than 1.96 were observed for utilization from District C to District A (3.69), from District G to District D (9.95), from District B to out of area providers (7.98), and from District E to out of area providers (5.78). For group screening, the absolute value of the adjusted standardized residual exceeded 1.96 only in District A (-2.05).

3.3 Spatial Clusters of Elevated HbA1c

The spatial scan analysis identified three clusters with relative risks greater than 1 (Table 3 and Figure 1). Cluster 1 comprised 40 chome units and included a population of 9,577 adults aged 40–74 years. The number of observed cases of elevated HbA1c was 400, compared with 315.80 expected cases. The observed to expected ratio was 1.27, and the relative risk was 1.37. Cluster 1 was statistically significant ($p < 0.01$).
Cluster 2 comprised 10 chome units and included a population of 4,986 adults. The number of observed cases was 209, compared with 164.41 expected cases. The observed to expected ratio was 1.27, and the relative risk was 1.32. Cluster 2 was not statistically significant ($p > 0.05$).
Cluster 3 comprised three chome units and included a population of 177 adults. The number of observed cases was 13, compared with 5.84 expected cases. The observed to expected ratio was 2.23, and the relative risk was 2.24. Cluster 3 was not statistically significant ($p > 0.05$).

		Provider District									
		A	B	C	D	E	F	G	Out of area	Group screening	Total
Residential district	A	401 (72.5%)	1 (0.2%)	4 (0.7%)	9 (1.6%)	2 (0.4%)	53 (9.6%)	0 (0.0%)	62 (11.2%)	21 (3.8%)	553
	B	140 (17.2%)	174 (21.4%)	5 (0.6%)	92 (11.3%)	19 (2.3%)	30 (3.7%)	2 (0.2%)	297 (36.5%)	55 (6.8%)	814
	C	172 (35.7%)	40 (8.3%)	33 (6.8%)	19 (3.9%)	38 (7.9%)	32 (6.6%)	0 (0.0%)	114 (23.7%)	34 (7.1%)	482
	D	31 (8.3%)	9 (2.4%)	2 (0.5%)	194 (52.2%)	4 (1.1%)	30 (8.1%)	8 (2.2%)	75 (20.2%)	19 (5.1%)	372
	E	93 (21.8%)	9 (2.1%)	0 (0.0%)	5 (1.2%)	119 (27.9%)	19 (4.5%)	0 (0.0%)	159 (37.3%)	22 (5.2%)	426
	F	65 (19.9%)	2 (0.6%)	3 (0.9%)	33 (10.1%)	2 (0.6%)	136 (41.7%)	0 (0.0%)	69 (21.2%)	16 (4.9%)	326
	G	16 (7.0%)	13 (5.7%)	1 (0.4%)	80 (35.2%)	2 (0.9%)	14 (6.2%)	35 (15.4%)	53 (23.3%)	13 (5.7%)	227
Total		918 (28.7%)	248 (7.8%)	48 (1.5%)	432 (13.5%)	186 (5.8%)	314 (9.8%)	45 (1.4%)	829 (25.9%)	180 (5.6%)	3,200

Table 1. Distribution of provider location categories according to residential elementary school district, n (%)

		Provider District								
		A	B	C	D	E	F	G	Out of area	Group screening
Residential district	A	25.05	-7.32	-1.65	-8.98	-6.02	-0.2	-3.09	-8.67	-2.05
	B	-8.39	16.84	-2.41	-2.13	-4.91	-6.81	-3.26	7.98	1.62
	C	3.69	0.49	10.48	-6.66	2.11	-2.54	-2.84	-1.23	1.48
	D	-9.23	-4.09	-1.62	23.21	-4.15	-1.21	1.3	-2.69	-0.46
	E	-3.36	-4.67	-2.74	-8	20.96	-3.99	-2.65	5.78	-0.44
	F	-3.69	-5.09	-0.91	-1.88	-4.23	20.43	-2.28	-2.06	-0.59
	G	-7.48	-1.18	-1.36	9.95	-3.29	-1.92	18.6	-0.91	0.07

Table 2. Adjusted standardized residuals for the association between residential district and provider location category

Cluster	Number of units	Population	Observed/ expected	Relative risk	p
1	40	9,577	1.27	1.37	< 0.01
2	10	4,986	1.27	1.32	> 0.05
3	3	177	2.23	2.24	> 0.05

Table 3. Spatial clusters of elevated HbA1c identified using the Poisson spatial scan statistic

Figure 1. Spatial distribution of clusters of elevated HbA1c identified at the chome level.

4. Discussion

4.1 Principal Findings

This study applied two geographic analyses to 3,200 records from Japan's Specific Health Checkups program in a single local government area. The provider catchment analysis showed a statistically significant association between residential district and provider location category. Utilization of providers located within the residential district was more frequent than expected in all seven districts. However, the distribution of provider use was not uniform. Within district use ranged from 6.8% to 72.5%, and out of area use ranged from 11.2% to 37.3%. Some districts were characterized primarily by within district utilization, whereas others showed greater use of providers outside the study area or in another district.

The spatial scan analysis identified one statistically significant cluster of elevated HbA1c at the chome level. The cluster included 400 observed cases compared with 315.80 expected cases and had a relative risk of 1.37. Two additional areas had relative risks greater than 1 but were not statistically significant. These two areas should not be interpreted as established clusters on the basis of the present analysis.

The provider catchment analysis and spatial scan analysis addressed different questions at different geographic scales. The former described where residents received preventive checkups, whereas the latter identified an area in which elevated HbA1c was geographically concentrated relative to the population denominator. Presenting these findings within the same study does not establish that provider utilization patterns caused or explained the observed cluster. Rather, the results show that local health risks and preventive service utilization cannot be assumed to be spatially homogeneous within a local government area.

Previous studies have examined geographic variation in health checkup utilization, access to preventive services, and metabolic risk using different spatial units and analytical approaches (Fujita et al., 2017; Fukuoka et al., 2021; Mizutani et al., 2024). The present study adds a local application using routinely collected checkup data at geographic scales that can be interpreted in relation to district based public health nursing activities.

4.2 Implications for Public Health Nursing Practice

The findings have several implications for public health nursing practice. First, the variation in provider catchment patterns indicates that residential district boundaries do not fully represent the preventive service pathways used by residents. Although within district utilization was more frequent than expected in all seven districts, the proportion varied markedly, and some districts had substantial out of area utilization or use of providers located in another district. When planning communication strategies or collaboration with clinical providers, public health nurses may therefore need to consider observed service utilization patterns rather than relying solely on administrative boundaries.

Second, the statistically significant chome level cluster of elevated HbA1c provides information that may support prioritization within the study area. The present analysis does not identify individual residents requiring intervention, nor does it establish that a particular outreach strategy would improve outcomes. However, aggregated spatial information can be used as one source of evidence when determining where additional assessment, communication, or coordination with providers may be warranted.

These implications are relevant to the future direction of public health nursing in Japan. The Ministry of Health, Labour and Welfare has indicated that public health nursing activities toward 2040 should be planned with attention to regional variation, prioritization, and the effective and efficient use of limited resources. The revised national guidance also emphasizes the collection, analysis, and sharing of local health information, the use of information and communication technology, and coordination with relevant departments and institutions (Ministry of Health, Labour and Welfare, 2026a, 2026b).

The workflow applied in this study provides one example of how routinely collected data already held by local governments can be used for these purposes. Specific Health Checkups data can be summarized at locally relevant geographic scales, examined using open geospatial tools, and presented in a form that supports discussion among public health nurses, administrative staff, and clinical providers. The present study did not evaluate changes in workload, cost, or health outcomes. Nevertheless, the use of existing data for geographic assessment may provide a practical basis for more focused planning as local governments prepare for changes in population structure and service needs toward 2040.

4.3 Methodological Contribution, Open Source Tools, and Capacity Building

The methodological contribution of this study lies in the use of routinely collected local government data for two transparent geographic analyses conducted at scales relevant to public health nursing practice. The origin destination table described provider utilization patterns at the elementary school district level, while the spatial scan analysis identified chome level concentrations of elevated HbA1c. Each analysis can be reproduced using aggregated tables, boundary data, and documented parameter settings without mapping individual residential locations.

The workflow used QGIS, R, and SaTScan. QGIS and R are free and open source software, and SaTScan is distributed free of charge with publicly available source code. The use of these tools has practical relevance for local governments. It can reduce dependence on proprietary software licenses and allow workflows to be adapted to local data structures. Procedures can also be shared across departments, local governments, and educational settings. These advantages may be particularly relevant to municipal public health nurses, who often need to analyze locally held data while working within limited financial and human resources. However, access to software alone is insufficient. Secure data governance, quality assurance, technical support, and staff training remain necessary.

The educational implications are increasingly important. Previous studies have described the use of GIS in public health nursing education and in the planning of population based interventions (Riner et al., 2004; Caley, 2004). In addition, natural language interfaces for GIS are emerging. For example, plugins listed in the official QGIS repository enable large language models to manage layers, edit features, execute processing algorithms, and render maps (QGIS Python Plugins Repository, 2026). Such tools may lower procedural barriers to GIS use, but automated operations require human verification, appropriate data protection measures, and evaluation before they are applied to municipal health data.

As assisted GIS operations develop, public health nursing education should not focus solely on software operation. Students and practitioners need to understand spatial units, data quality, confidentiality, analytical assumptions, reproducibility, and the interpretation of geographic results. Structured introductory approaches such as G-CHAM may provide one option for incorporating GIS based community health assessment into public health nursing education and continuing professional development (Horiike, 2025). Future studies should evaluate whether such training improves the ability of public health nurses and students to conduct reproducible analyses and use the findings appropriately in local planning.

4.4 Limitations

This study has several limitations. First, the analysis was conducted using data from a single local government area during one fiscal year. The observed provider catchment patterns and spatial clusters may reflect local population characteristics, provider distribution, and service delivery arrangements. The findings should therefore not be generalized directly to other local governments without further examination.

Second, the Poisson spatial scan analysis used the number of residents aged 40–74 years as the population denominator rather than the number of Specific Health Checkups participants in each chome unit. Spatial variation in checkup participation may have influenced the detected clusters. For example, an area with a comparatively high participation rate may have a larger number of observed cases even when the underlying prevalence of elevated HbA1c is similar to that of other areas. Where chome level participant denominators are available, additional analyses using these denominators should be conducted to assess the robustness of the findings.

Third, the spatial scan analysis was based on chome level aggregated data and polygon centroids. The results identify geographic concentrations at the area level and cannot be interpreted as evidence regarding the risk of individual residents. The use of aggregated geographic units may also affect the locations and sizes of detected clusters. In addition, circular scanning windows may not fully represent clusters with irregular spatial shapes.

Fourth, provider catchment patterns were summarized using elementary school districts and broad provider location categories. This approach was suitable for describing district level patterns but did not examine variation among individual provider institutions. The present analysis also did not directly test whether residents within the statistically significant HbA1c cluster used particular provider institutions or service channels more frequently than residents outside the cluster.

Fifth, elevated HbA1c was defined as HbA1c $\geq$ 5.6% and treated as an indicator of increased diabetes risk. This threshold does not represent a clinical diagnosis of diabetes. The findings should be interpreted as geographic variation in an indicator relevant to preventive health activities rather than as the spatial distribution of diagnosed diabetes.

Finally, this study did not evaluate whether the workflow reduced workload, improved resource allocation, increased the uptake of preventive services, or improved health outcomes. The potential use of open source GIS tools, assisted GIS operations, and educational approaches such as G-CHAM requires further evaluation in public health nursing practice and education.

5. Conclusions

This study applied provider catchment analysis and spatial scan statistics to records from Japan's Specific Health Checkups program in a single local government area. Provider utilization patterns differed across residential districts, and one statistically significant chome level cluster of elevated HbA1c was identified. These findings show that routinely collected preventive health data can be analyzed with open source geospatial tools to describe both service use patterns and small area risk concentration. The workflow does not replace professional judgment or local knowledge, but it can provide structured evidence to support public health nursing assessment, planning, and provider collaboration. As local governments prepare for changing population structures and service needs toward 2040, reproducible GIS based analysis of existing data may become an important component of evidence informed public health nursing practice and education.

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