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Bayesian Shared Component Spatial Modeling for Assessing the Shared and Age Group-Specific Mental Health Disorder Risk of Young and Old Age Groups: A Case Study of Toronto Neighborhoods, Canada

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Abstract: Mental health disorder risks of young and old age groups hold considerable importance for understanding present and future risk burdens. However, assessing mental health risks is significantly constrained by the influence of shared and age group-specific spatial processes and risk factors. Therefore, this study employed Bayesian shared component spatial modeling (BSCSM) to analyze mental health disorder data obtained from young (20–44 years) and old (65+ years) age groups in Toronto. BSCSM was employed to model the shared and age group-specific disorder risk and to identify hotspot areas. The unmeasured covariates, overdispersion, and latent spatial processes were adjusted using spatial and non-spatial random effect terms. The findings from BSCSM were finally compared with non-shared component modeling approaches. The results suggest that over 60% of variations in mental health disorder risk for both age groups could be explained by the shared component. The high-risk neighborhoods were mainly localized in southern and north-central Toronto for the young and old age groups. Deviance information criterion values suggested that models from BSCSM outperformed non-BSCSM models. BSCSM risk maps were also better at identifying high-risk areas. This work demonstrated that both shared and age group-specific risks are essential for assessing mental health disorder risk and devising targeted interventions.

Keywords: Bayesian; shared component spatial modeling; risk assessment; mental health disorders; young and old age groups; neighborhoods

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1. Introduction

Although strong evidence suggests that the age of individuals could influence the prevalence of mental health disorders in a society [1–3], how the spatial risk varies amongst young and old age groups of a population remains to be thoroughly understood. The mental health conditions of individuals change throughout life [4–6] and are affected by socioeconomic conditions [4,7], access to quality mental health care [8,9], and exposure to different physical and built environment factors [10,11]. Hence, the mental health risk in an area can be considered as a function of the spatially explicit risk factors and processes that affect the mental health status of individuals in a population [5,8,10,12]. Therefore, this study attempts to understand the shared (common) and age group-specific mental health disorder risk amongst young (20–44 years) and old (65+ years) age groups in Toronto, Canada, as conditioned by the spatially varying processes and risk factors.

The mental health risk in young and old age groups in Canada is of considerable interest as it helps us understand the present and future mental health burdens in Canada. In 2020, about 10% of the respondents in the Canadian Community Health Survey reported that their perceived mental health status was either fair or poor [13]. When the ages of the respondents are categorized into four major groups, for the same survey, it is found that

8.3% of the children and adolescents (12–17 years), 23.6% of the youths (18–49 years), 9% of the middle-aged (50–64 years), and 5.5% of the elderly (65+ years) respondents had reported fair or poor mental health conditions. Although the present figures suggest that the young population is the most vulnerable age group and the older population is relatively at less risk, with population aging and changes in the country's demographic structure, the scenario is likely to change rapidly [14,15]. In particular, when a large proportion of the population ages and joins the old age group, a shift in the age-related vulnerability for mental health disorders may occur within the Canadian population.

Unfortunately, studying the combined spatial risk patterns of mental health disorders in young and old age groups is not straightforward. First, mental health studies need to distinguish between the processes that are distinct to the young and old age groups and those that are common or shared. Second, the nature of factors governing the variations in these spatial processes must be understood. Third, the differences in outputs caused by applying statistical models that can differentiate the spatial unconformities in risk surfaces from those that cannot distinguish these spatial variations should be considered while selecting an appropriate risk assessment technique. In this regard, selecting a suitable analytical technique could play a vital role in detecting age-specific risk patterns, which could otherwise be obscured by the shared component of spatial risk.

The different age groups in a population may exhibit differential susceptibility to the mental health risk factors in an area. For example, mental health problems in young people are strongly dependent on their childhood experiences and early exposure to various environmental and socioeconomic factors. Kisley, Strathern, and Najman (2020) collected child abuse and maltreatment data from 2861 young adults in Australia and found a strong relationship between maltreatment and poor mental health conditions in individuals during their youth [16]. Their study also reported that most forms of maltreatment in childhood were directly linked with depressive and anxiety symptoms in young adults. At the same time, post-traumatic disorders (PTSDs) in later phases of life were found to be strongly associated with all forms of childhood abuse. Thus, areas with a lack of social support for children and strict policies against child abuse may experience elevated risk of mental health disorders among the youths. These findings from past studies also provide evidence that the existence or absence of some spatial processes (such as social support for children) may aggravate specific mental health risk factors (such as child abuse) and lead to age-specific mental health risks (such as depression in youths) in an area.

Likewise, when considering natural and built environment risk factors, the mental health of young individuals showed contrasting responses compared to the mental health of seniors. For example, young people interact more with greenspaces in outdoor environments for relaxation, physical exercises, and social gatherings [11,17–19]. Therefore, young individuals are likely to be significantly affected by increased exposure to surrounding vegetation cover and may even experience better mental health outcomes than other age groups [10,20,21]. In contrast, past studies have indicated that socioeconomic factors like unemployment and deprivation could substantially affect older citizens [4,7,22], suggesting their mental health could be relatively less influenced by natural and built-environment factors, such as exposure to vegetation cover [23,24].

Similar to the young age group, there are mental health processes and risk factors unique to the old age group. Compared to young people, older individuals are more adversely affected by age-related ill-health, social isolation, and a lack of support during the final years of their lives [25,26]. Consequently, older people may experience severe mental health issues, often leading to suicide and self-harm tendencies [25]. After assessing the self-harm records of 465,870 individuals in long-term care facilities and 773,855 people at care home facilities in Canada, Chai et al. (2021) concluded that individuals from the 60–74 year age group were particularly prone to self-harm due to various psychiatric disorders [26]. On this issue, Perlman et al. (2019) showed that older citizens in Canada might not adequately receive psychiatric and mental health support when required. Their study reported that only 4.7% of the study participants, residing in long-term care homes in

Ontario (2015 to 2016) and having identified psychiatric needs, had received any psychiatric service within 90 days following cohort entry [27]. Hence, areas with such reduced access to mental health services can experience high mental health disorder risk amongst the older age group in the population. This risk is substantially different from the risk in younger age groups since mental health complications owing to geriatric problems are unique to older people.

Therefore, risk modeling techniques are faced with the tremendous challenge of addressing the age group-specific variations (similarities and uniqueness) in processes and risk factors that govern the distribution of mental health disorder cases in an area. In this regard, the joint statistical models could be particularly useful for assessing the conjoint or shared mental health risks that allow the analysis of multiple mental health outcomes in a single model [28,29]. Due to the conjoint modeling approach, age group-specific variations (similarities and uniqueness) in processes and risk factors could be simultaneously considered to derive accurate risk estimations. Several such modeling techniques are now in use, which include Bayesian Poisson, negative binomial, conditional autoregressive, and spatiotemporal conditional autoregression with ANOVA models [30–33]. However, the Bayesian shared component spatial modeling (BSCSM) technique has garnered substantial attention in health studies.

In particular, BSCSM is preferred over existing methods as it can adjust spatial dependencies amongst cases due to the neighborhood effect and spatial heterogeneities in risk-generating processes caused by the uneven distribution of risk factors and differential susceptibility of mental health outcomes towards a given set of risk factors. Moreover, BSCSM accounts for model or process uncertainties generated due to the simplification of real-life processes by statistical models. Finally, it addresses any data sparsity issues caused by a small population or low counts of cases [8,28,34]. Although various spatial risk assessment techniques have been employed in the past, such as the spatial-point pattern analysis [35], spatial error and lag models [36,37], geographically weighted regression [38,39], and Bayesian geoadditive quantile [40] and Poisson regression techniques [10,41,42], the use of joint models has been quite limited in mental health studies [8].

Hence, to address the research gap in analyzing the shared and age-group-specific mental health disorder risk in young and old age groups, this study adopted a Bayesian hierarchical joint modeling approach. Specifically, this study applied BSCSM to evaluate mental health disorder risk in young and older adults in the Toronto neighborhoods of Canada.

Thus, the study aimed to fulfill the following three objectives:

(a) Assess the spatial variations in the mental health disorder risks of young (20–44 years) and old (65+ years) age groups in Toronto neighborhoods;
(b) Analyze the differences in shared and age-group-specific mental health disorder risk patterns;
(c) Understand the benefit of adopting the BSCSM approach for a detailed understanding of the spatial variations in mental health risk.

2. Materials and Methods

2.1. Study Area and Data

The study area is the City of Toronto in Canada. The spatial unit is the neighborhood level, which are areal units constructed by the Social Development and Administration Division of the City of Toronto for planning and service deliveries [10,43]. A total of 140 neighborhoods (populations ranging from 7000–10,000) in the study area were incorporated into the analysis. The analyzed data comprised the observed mental health disorder cases in the Toronto neighborhoods from 1 April 2015 to 31 March 2016 (Fiscal year, 2015). The data were generated from the study "Enrollment, Access, Continuity, and Mental Health Gaps in Care (Project No. 2018 0900 992 000)" by the Institute for Clinical Evaluative Sciences (ICES) and funded by the Ontario Ministry of Health and Long-Term

Care (MOHLTC) [44]. The data are publicly available from the Ontario Community Health Profiles Partnership database [45].

The study population comprised all Ontario permanent residents eligible for coverage under the Ontario Health Insurance Plan (OHIP) on 31 March 2016. The mental health disorder cases were measured using outpatient OHIP visits/claims. The cases for which the ICES key number could not be validated were excluded. The ICES key number is the primary unique and encrypted identifier for every individual generated from the OHIP number. Furthermore, cases with ages over 105 years, residing in long-term care and complex continuing care during the study period, deaths before 31 March 2016, and no contact within eight years before 31 March 2016 were excluded from the cohort.

The mental health disorder dataset was categorized into four major age groups: 0–19, 20–44, 45–64, and 65+ years. For this study, the observed case data of the age groups 20–44 and 65+, including both sexes (males and females), were used. Furthermore, the expected cases in each neighborhood (E_i) were computed from the observed cases through the indirect standardization method. The process involved first calculating the overall rate of mental health disorders for each age group separately and then multiplying it with the residential population of each neighborhood. These expected counts allowed the Bayesian models to account for the population at risk, and the indirect standardization method allowed sex-specific disorder rates to be adjusted within the Bayesian models [10,46].

The cases in the original dataset are based on four major disorder categories, which are psychotic, non-psychotic, substance use, and family, social, and occupational issues related to mental health disorders. The four categories are, in turn, generated from the sub-categories based on the OHIP codes:

(1) Psychotic disorders: schizophrenia (295); manic-depressive psychoses, involutional melancholia (296); other paranoid states (297) and psychoses (298)
(2) Non-psychotic disorders: anxiety neurosis, hysteria, neurasthenia, obsessive-compulsive neurosis, and reactive depression (300); personality disorders (301); sexual deviations (302); psychosomatic illness (306); adjustment reaction (309) and depressive disorders (311)
(3) Substance use disorders: alcoholism (303) and drug dependence (304)
(4) Family, social and occupational issues: economic problems (897); marital difficulties (898); parent–child problems (899); problems with aged parents or in-laws (900); family disruption/divorce (901); education problems (902); social maladjustment (904); occupational problems (905); legal problems (906) and other problems of social adjustment (909)

The mental health disorder dataset that was used in the BSCSM analyses contained aggregated data on all four major categories (and their sub-categories) listed above, providing an extensive range of mental health disorder categories and a refined picture of the mental health disorder risk in the study area [44].

2.2. Assessing the Spatial Variations in Mental Health Disorders Risks: Modeling Techniques

The study adopted a Bayesian shared component spatial modeling (BSCSM) approach to model the two outcomes of mental health disorders of young (20–44 years) and old (65+ years) age groups. The mental health disorder case counts, denoted by O_{ik}, were assumed to follow a Poisson distribution and conditioned on the mean μ_{ik}; $O_i \sim Poisson(\mu_{ik})$. Here, i represents the neighborhood areas (i = 1, 2, …, 140), and k represents the two outcomes or age groups of mental health disorders (k = 1 and 2, where 1 = young and 2 = old age group). The Poisson distribution was considered as it is suitable for the Bayesian modeling of small-area data, where random effects could be used for adjusting overdispersion and residual spatial correlations (dependency and heterogeneity) [47,48].

Equation (1) defines Model 1, where the observed mental health disorder cases, O_{ik}, is modeled as $Poisson(\mu_{ik})$. The Poisson mean, μ_{ik}, is, in turn, modeled as the sum of the log of expected cases (E_i), the baseline risk of mental health disorders in the study area (α_k), a spatial shared component for the two age groups $(\lambda_k\theta_i)$ that models the shared

processes and risk factors influencing the distribution of cases [49], an outcome-specific spatial random effect term (s_{ik}), and a non-spatial random effect term (u_{ik}) that models the spatial processes and the non-spatial processes unique to each age group, respectively. For more information on how E_i is computed, please see Section 2.1.

$$\log(\mu_{ik}) = \log(E_i) + \alpha_k + \lambda_k\theta_i + s_{ik} + u_{ik} \quad (1)$$

The spatial shared component $\lambda_k\theta_i$ is comprised of the risk gradient $(\lambda_k$, where $\lambda_k > 0)$ and the spatially structured and shared random effect term (θ_i). The risk gradient (often called the 'scaling parameter') allows a unique association between the mental health disorders in each age group and the shared component. In other words, the risk gradient identifies the relative contribution of each age group (or outcome) to the shared risk [50,51].

As model identifiability is improved when the risk gradient of one outcome is the inverse of the other outcome [34,52], we inversed the risk gradient for the second outcome or for the old age group. Hence, $\lambda_1 = \lambda$ and $\lambda_2 = \frac{1}{\lambda}$ were implemented in the models. Under such criteria, a λ value closer to 1 would imply that the risk gradient for the shared component of the two age groups is almost equal or that the two age groups had equal contributions to the shared risk [8]. Alternatively, a high and positive value of λ would imply that the mental health disorder risk of young people contains a more significant proportion of the shared risk compared to the older adults.

The shared risk $(r.shared_{\ i})$ of mental health disorders was computed to understand the spatial risk patterns shared by the two age groups (Equation (2)). Moreover, the age group-specific spatial and non-spatial risk $(r.specific_{\ ik})$ was modeled by analyzing age group-specific spatial and non-spatial random effect terms (Equation (3)).

$$r.shared_{\ i} = \exp(\theta_i) \quad (2)$$

$$r.specific_{\ ik} = \exp(s_{ik} + u_{ik}) \quad (3)$$

It is important to note that it is also possible to incorporate different covariates or risk factors in the BSCSM models as defined in Equation (1) [47]. This could potentially adjust for the effect of putative risk factors in risk assessments in Equations (2) and (3). However, since the primary objective of this study is to assess the shared and age-group-specific mental health disorder risk amongst young and old age groups, no covariates were necessary for the shared component models. Under these criteria, when no covariates are incorporated in the BSCSM, the s_{ik} and u_{ik} random effect terms capture the effects of all unmeasured putative risk factors. Thus, the estimated relative risk, $r.shared_{\ i}$ or $r.specific_{\ ik}$, becomes a product of all the risk factors operating within the study area [53].

The relative importance of the shared component was analyzed by estimating the fraction of the total variation in log-relative risk explained by the shared component (ϕ_k).

$$\phi_k = \frac{\mathrm{Var}(\lambda_k\theta_i)}{\mathrm{Var}(\lambda_k\theta_i) + \mathrm{Var}(s_{ik} + u_{ik})} \quad (4)$$

Here, $\mathrm{Var}(\lambda_k\theta_i)$ represents the empirical variance of the shared component and $\mathrm{Var}(s_{ik} + u_{ik})$ represents the empirical variance of the outcome-specific components.

For establishing the necessity of adopting the BSCSM approach, the mental health disorder risks of the young and old age groups in Toronto were also analyzed using the crude standardized risk ratios (observed cases/expected cases) and the Bayesian non-shared component spatial modeling (BNSM) approach. Similar to BSCSM, in the BNSM approach, the mental health disorder case counts were assumed to follow a Poisson distribution and conditioned on the mean μ_{ik}; $O_{ik} \sim Poisson(\mu_{ik})$. The Poisson mean, μ_{ik}, was then modeled as the sum of the log of expected cases (E_i), the baseline risk of mental health disorders in the study area (α_k), the spatial random effect (s_{ik}), and a non-spatial random effect term (u_{ik}).

$$\log(\mu_{ik}) = \log(E_i) + \alpha_k + s_{ik} + u_{ik} \quad (5)$$

Equation (5) was used to develop two separate models for the young (Model 2, where $k = 1$) and old (Model 3, where $k = 2$) age groups. The relative risk (r_{ik}) of mental health disorders for each age group (Equation (6)) was assumed to be a function of the baseline risk and the effect of the putative risk factors of mental health disorders $(s_{ik} + u_{ik})$.

$$r_{ik} = \exp(\alpha_k + s_{ik} + u_{ik}) \quad (6)$$

2.3. Assessing the Differences in Shared and Age-Group-Specific Mental Health Risk Patterns: The Hotspots of Mental Health Disorders

The hotspots are considered to be areas with a high risk of mental health disorders for the young and old age groups. Although different hotspot identification techniques are used in health studies, such as spatial scan statistics [54] and local indicators of spatial association [55], the BSCSM technique offers adjustments in the uncertainties in the estimates of area-specific risks [51].

The shared and age group-specific hotspots of mental health disorders, estimated using the BSCSM, were assessed to better detect the neighborhoods with a high risk of mental health disorders. The hotspots of shared risk were mapped based on the posterior probability of the shared random effect being greater than one ($\Pr(\exp(\theta_i) > 1 \mid O_{ik})$).

Similarly, the age group-specific hotspots were distinguished by modeling the posterior probability of the spatial and non-spatial random effects being greater than one ($\Pr(\exp(s_{ik} + u_{ik}) > 1 \mid O_{ik})$). To compare these age-specific hotspots from BSCSM with hotspots identified using BNSM, the posterior probability of the relative risk (r_{ik}) being greater than one ($\Pr(\exp(r_{ik}) > 1 \mid O_{ik})$) was also measured.

2.4. Defining Priors and Model Assessment Criteria

The prior selection was primarily based on the nature of the parameter to be estimated. In most cases, a non-informative prior was used when necessary. A normal prior was used for the baseline risk, α_k. Contrastingly, the spatial random effect terms, θ_i and s_{ik}, were assigned with the intrinsic normal conditional autoregressive (ICAR) prior distribution. A neighborhood weight matrix was employed in the ICAR, which helped define the conditional priors of the spatial random effect terms and adjust for the effect of spatial adjacency or neighborhood influence, such as spatial dependence and heterogeneity [8,56,57]. For more details on the neighborhood weight matrix and ICAR distribution implemented in this study, please consult Law and Perlman, 2018 [8]. The prior for the precision parameters of θ_i was Gamma (0.1, 0.1), whereas Gamma (1, 0.01) was used for the s_{ik} and u_{ik} terms. Additionally, a sensitivity test was run using different sets of hyperpriors for the precision parameters, where all the spatially structured random effect terms were assigned with Gamma (0.1, 0.1), and the unstructured random effects were assigned with Gamma (0.01, 0.01) parameters. The results were similar; hence, based on the deviance information criterion (DIC) values, the priors for the precision parameters were finalized [53,58]. Furthermore, the logarithm of the risk gradient, λ_k, was assumed to have a normal prior with a mean of 0 and a precision of 5.9 [8,34].

The models were implemented using the WinBUGS software (version 1.4.3) [59], and two chains at dispersed starting values were converged using Markov Chain Monte Carlo (MCMC) simulations. The trace plots, Gelman–Rubin convergence statistics, and autocorrelation graphs were monitored to ensure model convergence. The MCMC simulations were run until the MC error for each parameter was less than 5% of the sample posterior standard deviation to ensure sampling sufficiency [46].

In order to establish a comparison between the BSCSM and BNSM, the DIC for each model was considered. The DIC is a sum of the model fit and the model complexity, where an increase in model complexity also increases the DIC values. Therefore, as parsimonious models are preferred in modeling practices because they have greater predictive power, are relatively incomplex, and have the minimum number of parameters [60], we considered models with lower DIC values as the better models. It is important to note that lower

DIC values do not establish the superiority of one model over the other; the comparison is purely relative and based on the principle of the parsimonious model.

3. Results

3.1. The Spatial Variations in Mental Health Disorder Risks: Shared and Age Group-Specific Risks

The mental health disorder risks of the young (20–44 years) and old (65+ years) age groups, estimated using BSCSM (Model 1), are illustrated in Figure 1. Figure 1 shows that the age group-specific risks for the young (Figure 1a) and old (Figure 1b) age groups substantially differ from one another. The mental health disorder risk of the young age group extends from the east to the west of the study area, while the risk for the old age group spans from the north to the southern parts of Toronto. The moderately high and high-risk neighborhoods ($r.specific_{ik} > 1.1$) for the young age group are mainly located in the southeastern region of the study area. In contrast, central Toronto corresponds to moderately high and high-risk zones. However, the mental health disorder risk for both age groups (Figure 1c) is substantially high in southcentral Toronto compared to any other area.

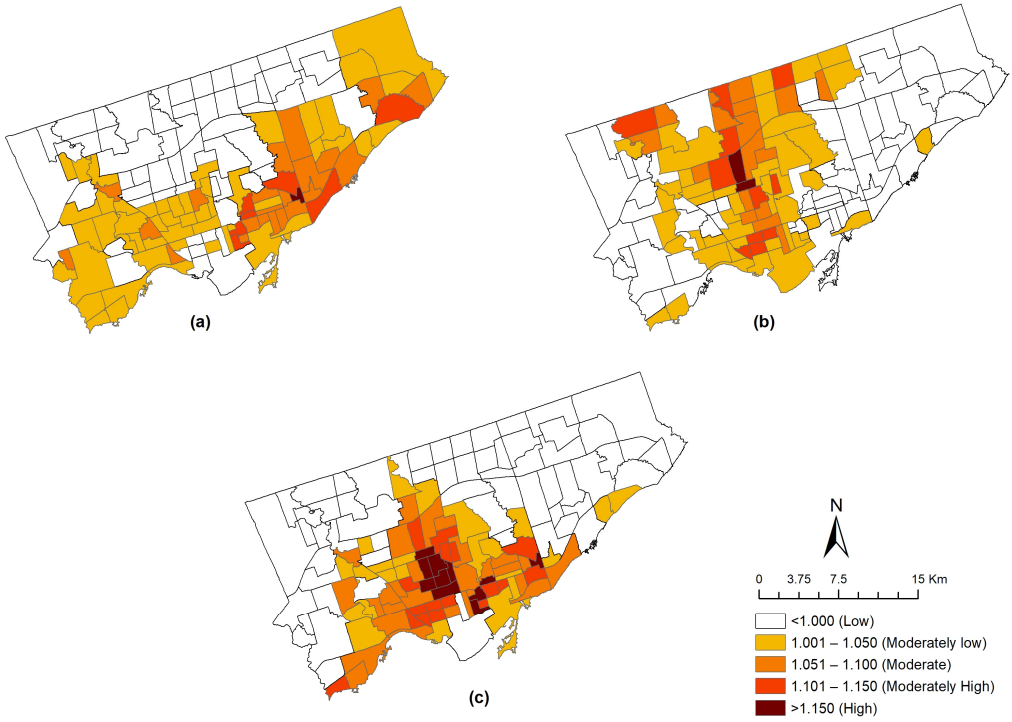

Figure 1. The mental health disorder risk in Toronto neighborhoods, showing the (**a**) outcome-specific risk for the young age group ($\exp(s_{i1} + u_{i1})$), (**b**) outcomespecific risk for old age group ($\exp(s_{i2} + u_{i2})$), and (**c**) risk shared by both young and old age groups ($\exp(\theta_i)$).

The spatial patterns in risk maps can be better understood using Table 1. The fraction of total variation in relative risks that can be explained by the shared component was 0.678 (95% CI: 0.365, 0.905) for the young age group and 0.635 (95% CI: 0.315, 0.896) for the old age group. Therefore, it is evident that the shared component of the risk significantly contributed to 67.8% and 63.5% of the total variation in the relative risk of mental health disorders for young and older people, respectively. The risk gradient (λ_k) has a value of 1.077 (95% CI: 0.825, 1.372), which shows that the contribution to the shared risk was almost equal for both age groups. Consequently, the spatial patterns observed in the age group-specific risk maps became distinct due to filtering out the high contributions from the shared component in spatial risks.

Table 1. The WinBUGS results of the Bayesian shared component spatial risk modeling of mental health disorders for young and old age groups in Toronto (Model 1): the posterior means and credible intervals (2.5–97.5%) of the risk gradient and empirical variances.

	Young Age Group (20–44 Years), k = 1	**Old Age Group (65+ Years), k = 2**
Risk gradient (λ_k)	1.077 (0.825, 1.372)	0.945 (0.730, 1.212)
Empirical variances		
Young and old age groups' shared effects: Var $(\lambda\theta_i)$ for $k = 1$; Var$\left(\frac{1}{\lambda}\theta_i\right)$ for $k = 2$	0.019 (0.009, 0.03)	0.0148 (0.006, 0.025)
Young and old age group-specific effects (spatially structured and unstructured random effects combined): Var$(s_{ik} + u_{ik})$	0.009 (0.003, 0.016)	0.008 (0.003, 0.015)
The fraction of total variation in relative risks that can be explained by the shared component (ϕ_k):	0.678 (0.365, 0.905)	0.635 (0.315, 0.896)
The fraction of total variation in relative risks that can be explained by the age group or outcome-specific effects:	0.323 (0.095, 0.636)	0.365 (0.103, 0.686)
The deviance information criterion (DIC)	1458.590	1327.250

Figure 2 displays the mental health risk maps for the young age group. Figure 2a represents a risk map developed using the non-shared component risk modeling approach, specifically using the crude standardized risk ratio method. The high-risk regions of the standardized risk maps (Figure 2a) belong to the moderate or moderately low-risk categories in the young age group-specific risk map generated using BSCSM (Figure 2b).

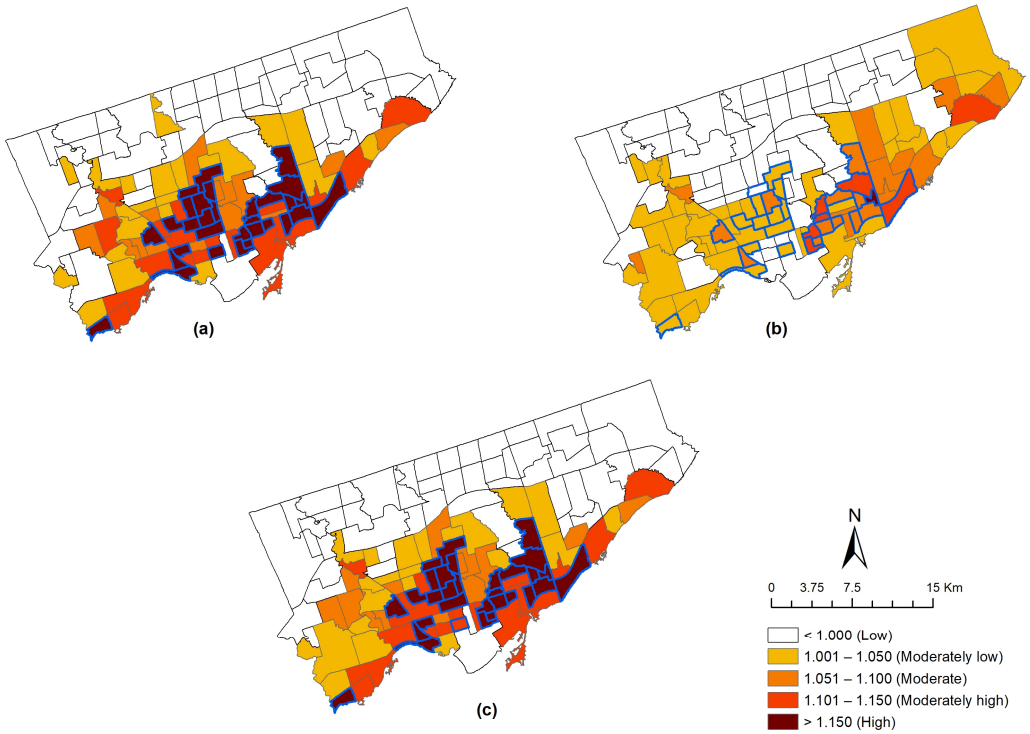

Figure 2. The mental health disorder risk in Toronto neighborhoods for the young age group, showing the (**a**) standardized risk (observed/expected cases), (**b**) outcome-specific risk from BSCSM (exp$(s_{i1} + u_{i1})$), and (**c**) general risk from BSNM (exp$(\alpha_1 + s_{i1} + u_{i1})$). The highlighted areas (blue boundaries) represent the high-risk areas identified using standardized risk ratios (standardized risk > 1.15).

A similar distinction could be observed between the young age group-specific map and the risk map produced from BNSM (Model 2) in Figure 2c. The BNSM risk map in Figure 2c is, visually, almost similar to the standardized risk maps in Figure 2a, with high-risk areas located mainly in the south-central parts of Toronto. This contrasts with the age group-specific map produced using BSCSM, where the moderately high and high-risk neighborhoods are located in southeastern Toronto. Furthermore, the number of neighborhoods with high mental health disorder risks for young people is considerably higher in maps estimated from the conventional non-shared component risk modeling approaches when compared to the BSCSM approach.

Table 1 shows that the fraction of total variation in relative risks specific to the young age group is only 32.2% (0.323; 95% CI: 0.095, 0.636). This implies that the non-shared risk modeling approaches could not differentiate this age-specific mental health disorder risk for young people from the risk shared with older individuals (67.8%). Consequently, Figure 2a,c shows a blend of risks from the young and the old age groups.

The mental health disorder risk maps for the old age group are shown in Figure 3. Similar to the risk maps for the young age group, the standardized risk map in Figure 3a, developed from the non-shared approach, can be easily distinguished from the BSCSM risk map in Figure 3b. The high-risk neighborhoods identified by the crude risk assessment are either at moderately low or moderate risk levels in the BSCSM map. The risk map (Figure 3c) developed from BNSM (Model 3) similarly contrasts with the BSCSM map and is almost identical to the standardized risk map. However, despite the apparent differences in risk levels, all neighborhoods with elevated mental health disorder risks for older people are located in the central parts of Toronto, specifically extending from the northern to the southern region. The fraction of total variation in relative risks specific to the old age group (Table 1) is 36.5% (0.365; 95% CI: 0.103, 0.686), which accounts for the observed differences between the maps generated from the non-shared component and the shared component approaches.

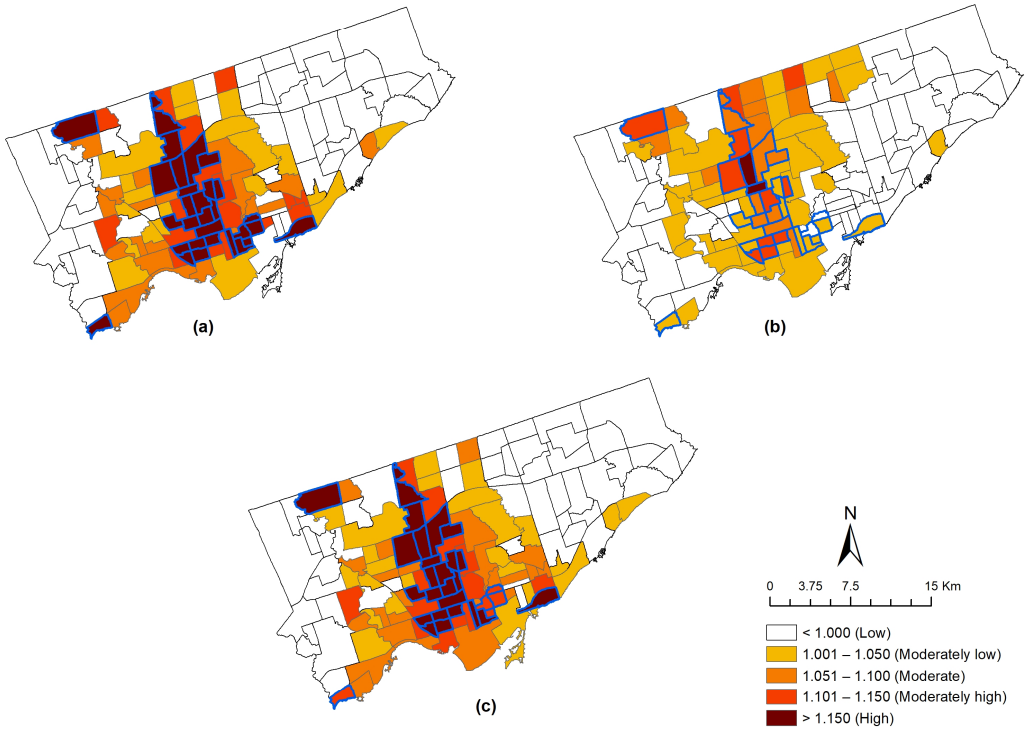

Figure 3. The mental health disorder risk in Toronto neighborhoods for the old age group, showing the (**a**) standardized risk (observed/expected cases), (**b**) outcome-specific risk from BSCSM ($\exp(s_{i2} + u_{i2})$), and (**c**) general risk from BSNM ($\exp(\alpha_2 + s_{i2} + u_{i2})$). The highlighted areas (blue boundaries) represent the high-risk areas identified using standardized risk ratios (standardized risk > 1.15).

The age group-specific DIC values for Model 1 (Table 1) could be compared with the DIC values for Model 2 and Model 3. The models estimating mental health disorder risk in the young and old age groups from the BSCSM have DIC values of 1458.59 and 1327.25, respectively. In contrast, the model from the BNSM has a DIC value of 1467.84 for the young age group and 1340.27 for the old age group. Consequently, the age group-specific models from the BSCSM have lower DIC values and are relatively better at modeling mental health disorder risks than those developed from the BNSM.

3.2. Differences in Shared and Age-Group-Specific Mental Health Risk Patterns: The Hotspots of Mental Health Disorders

Figure 4 displays the hotspots of mental health disorders in Toronto neighborhoods for the young and old age groups. The results display the outputs obtained from thresholding the posterior probability of relative risks in neighborhoods greater than 1 in the models from BSCSM and BNSM.

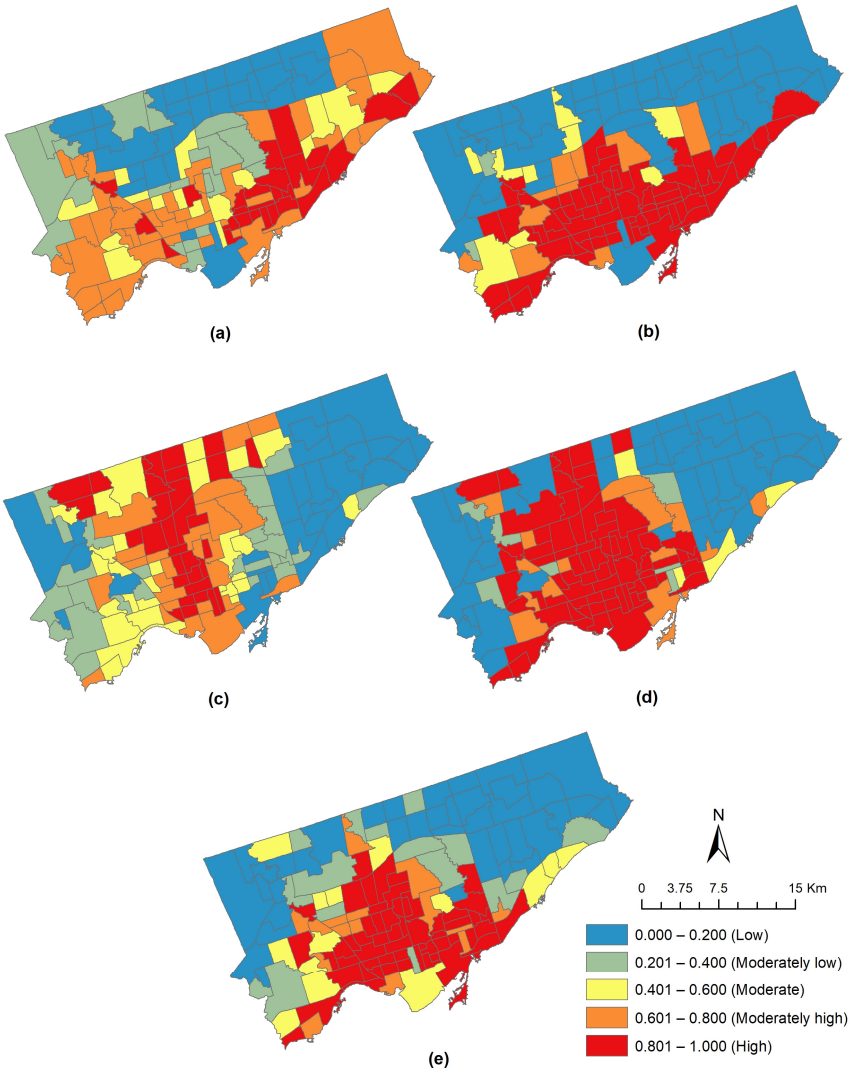

Figure 4. The hotspots of mental health disorders in Toronto neighborhoods for the young and old age groups. The hotspots have been identified from the (**a**) age group-specific risk for the young age group ($\Pr(\exp(s_{i1} + u_{i1}) > 1 \mid O_{i1})$), (**b**) BNSM of risk for the young age group (($\Pr(\exp(r_{i1}) > 1 \mid O_{i1})$), (**c**) age group-specific risk for the old age group ($\Pr(\exp(s_{i2} + u_{i2}) > 1 \mid O_{i2})$), (**d**) BNSM of risk for the old age group (($\Pr(\exp(r_{i2}) > 1 \mid O_{i2})$), and (**e**) the shared component risk for young and old age groups ($\Pr(\exp(\theta_i) > 1 \mid O_{ik})$).

Figure 4a,b represents the mental health disorder hotspots for the young age group. The hotspots in Figure 4a were identified using the age group-specific risks in BSCSM for the young age group ($\Pr(\exp(s_{i1} + u_{i1}) > 1 \mid O_{i1})$), while Figure 4b was produced using BNSM (($\Pr(\exp(r_{i1}) > 1 \mid O_{i1})$). The hotspot maps contrast considerably, especially in areas with high probabilities of mental health disorders. For the most part, the BSCSM hotspot map shows that the neighborhoods in the southeast to southwest direction had moderately high to high probabilities of developing mental health disorders. The neighborhoods identified as moderately low-risk areas in risk maps (Figure 2a) exhibited moderate to high probabilities of developing mental health disorders in the hotspot map (Figure 4a). In contrast, the BNSM hotspot map (Figure 4b) showed a lower probability gradient than the BSCSM hotspot map, with neighborhoods in the south exhibiting high probabilities of developing mental health disorders. A marked difference is also observed in some of the neighborhoods in the northern part of Toronto, which are labeled as hotspots in the BSCSM map but non-hotspot areas in the BNSM map.

Likewise, Figure 4c,d represents the mental health disorder hotspots for the old age group. The hotspots in Figure 4c were identified using the age group-specific risk in BSCSM for the old age group ($\Pr(\exp(s_{i2} + u_{i2}) > 1 | O_{i2})$). However, the hotspots of Figure 4d were detected using BNSM (($\Pr(\exp(r_{i2}) > 1 \mid O_{i2})$). Similar to the hotspot maps for the youths, the two hotspot maps for the older population contrast in terms of risk probability, with hotspots mainly located from the northern to the southern region of central Toronto. The hotspot map in Figure 4d shows relatively less gradation in risk probability compared to Figure 4c and has neighborhoods mostly labeled as either low or high-probability areas.

At last, Figure 4e illustrates the hotspots of shared component risk for young and old age groups ($\Pr(\exp(\theta_i) > 1 \mid O_{ik})$), developed solely using the BSCSM technique. The neighborhoods with high probabilities of mental health disorders in both age groups are primarily located in the south-central parts of Toronto. The neighborhoods adjacent to these hotspots also have a higher probability of developing mental health disorders compared to other areas and predominantly exhibit moderate to moderately high-risk probabilities.

4. Discussion

This study applied Bayesian shared component spatial modeling (BSCSM) to analyze the shared and age group-specific mental health disorder risk amongst young (20–44 years) and old (65+) age groups in Toronto neighborhoods. The results provide evidence that most of the variations in mental health disorder risk in the study area were caused by the risks shared by two age groups, with both groups contributing almost equally to the shared component of the spatial risk. However, differences in the age group-specific risk are also evident, highlighting the importance of considering both the shared and age group-specific risk to understand the mental health risk at the population level. Furthermore, findings suggest that conventional risk assessment techniques cannot filter out the risks shared by multiple age groups. Thus, risk maps are produced where age group-specific risks are diluted, and age group-specific spatial patterns are masked by the shared component of spatial risk. The DIC values of age group-specific models in BSCSM are smaller than those from individual Bayesian non-shared component models, suggesting better model developments using the BSCSM approach. Consequently, the findings contribute to the limited literature on how the shared and age group-specific processes and spatial risk factors may cause substantial variations in mental health risk for young and older adults. The results show the critical importance of the spatially shared component of risk, which is widely neglected in epidemiological studies.

The spatial variations observed in the shared and age group-specific mental health disorder risks could be better understood by considering the nature of underlying spatial processes and risk factors. First, our observed variations could originate from the uneven distribution or spatial heterogeneity of mental health risk factors in the study area, leading to the observed differences in risk amongst the neighborhoods [3]. For example, material deprivation is a socioeconomic risk factor that affects both the young and old

age groups [3,61,62]. Furthermore, past studies have reported that material deprivation varied geographically in Ontario, with more deprived areas experiencing elevated risks of mental illness and psychotic disorders [41,62]. These findings suggest that the risk factors, which had spatially varied amongst the neighborhoods in Toronto, could have potentially influenced the variations in the shared and age group-specific risks amongst the neighborhoods.

Second, the spatial variations in mental health disorder risks could stem from an evenly distributed set of risk factors having uneven effects on the mental health conditions of the young and old age groups. For example, the Toronto area is characterized by high urbanization and a predominant presence of built-up areas [10,63]. Hence, increased built-up areas can cause reduced exposure to nature, which is a common risk factor for poor mental health [10,11,20]. As past studies suggest that young people have higher chances of interacting with outdoor environments compared to older people [11,17–19], the effect of reduced exposure to nature could disproportionately affect the youths. Hence, the observed age group-specific variations in mental health disorder risks could be driven by these spatial processes, causing a distinction in the shared component of spatial risk.

Third, the observed variations in mental health risk may arise from the individual-level processes that aggregate together and influence the population-level processes [46]. For example, individual mental health risks may vary due to differences in age, genetic build-up, and health risk behaviors such as alcohol intake and substance abuse [5,7,9,46]. Although these processes are individual in nature, they add up and determine the overall risk in an area [46,64]. Therefore, variations in these individual-level processes can cause the population-level processes to become similar (shared) to the young and old age groups or unique (age group-specific) to each age group. For example, chronic pain (or daily severe pain) could significantly impair the mental health conditions of old individuals in Ontario [26]. Therefore, deterioration in mental health due to chronic pain in older people would be reflected in the population-level mental health data. This type of hierarchical process, where individual processes are directly linked with group-level processes, could have led to the distinctive age group-specific risk patterns in the study area [28].

Fourth, the variations can originate from the area-level processes that influence the case distributions amongst the neighbors and non-neighboring areas. For example, neighboring areas have more similarities with each other than those that are further away [65]. This proximity or 'neighboring effect' causes mental health cases to be spatially autocorrelated and exhibit a systematic spatial variation [3,66]. Consequently, the distribution of mental health cases in one area becomes dependent on the case distributions in the neighboring areas. This effect is evident from the observed clusters in our risk and hotspot maps. For example, the high-risk neighborhoods in both the shared and age group-specific maps are located near each other, with moderately high-risk neighborhoods surrounding the high-risk areas. This dependence structure is extremely important from an analytical perspective, as it should drive the selection of the risk assessment technique. Conventional statistical techniques, such as multivariable linear regression, heavily rely on the observed cases to be independent of each other. Consequently, when statistical models fail to adjust spatial dependence, parameter estimations are impaired, and uncertainties in parameter values are increased. Depending on the nature of the dependence structure amongst the cases, this may even lead to Type I and II errors in the results [28].

As demonstrated in this study, the use of BSCSM for mental health disorder risk assessment presents a number of advantages. First, due to the integration of the shared component term ($\lambda_k \theta_i$) in BSCSM, it is possible to identify areas where the young and old age groups share the risk of mental health disorders. These shared risk areas have spatial processes and risk factors common to both the young and old age groups, holding considerable significance from public health management perspectives. For example, our findings suggest that identifying and targeting the prominent risk factors in just the shared risk areas would have allowed us to address 67.8% of the variability in the mental disorder risk of youths and 63.5% of the risk in the elderly people of the Toronto area. This is both a

time and resource-economizing approach and allows targeted intervention strategies to be formulated to address mental health burdens in an area.

Second, as the BSCSM filters out the shared component of spatial risks, the random effect terms (s_{ik} and u_{ik}) can model the remaining age group-specific processes that deviate from the shared processes in the study area [8,67]. These age group-specific processes, in turn, can capture both the individual-level processes that lead to variations in population-level mental health risk and the area-level processes that lead to the spatial dependence of cases amongst the neighboring areas [34,49,53]. Moreover, these random effect terms also adjust for the unmeasured and latent covariates that influence the distribution of mental health disorder cases in the study area [8,49]. This is critically important as model or process uncertainties need to be adjusted by integrating all covariates that influence mental health disorder risk in an area [28]. However, since it is impossible to measure and incorporate all the influential covariates in risk assessment models, the integration of the random effect terms offers a reliable way to adjust for the unmeasured and latent covariates in the models [46]. In contrast, due to the missing shared component term, the s_{ik} and u_{ik} in BNSM simply capture the effects of the unmeasured covariates that are, respectively, spatially and non-spatially structured [46,53]. As a result, and contrary to BSCSM, the random effect terms in BNSM represent both the shared and age group-specific processes that influence the observed mental health disorder cases in the study area.

Lastly, the BSCSM offers the benefits of employing local statistical models for mental health risk assessment. Due to spatial heterogeneity in the underlying processes and risk factors, each area has its own set of parameter values; therefore, local models are required to estimate these area-specific unknown parameters [68,69]. The BSCSM allows the shared (exp (θ_i)) and age group-specific risks (exp$(s_{ik} + u_{ik})$) to vary based on the individual neighborhoods (i), allowing individual models to be fitted for each area and the adjustment of uncertainties caused by spatial heterogeneity [28]. Furthermore, contrary to non-Bayesian approaches, the application of the Bayesian framework in shared component modeling allows local models to consider spatial processes as an integral part of risk modeling [46]. This approach substantially differs from existing local spatial risk modeling approaches, such as the geographically weighted regression, where spatial processes are considered a nuisance and adjusted in the models as error residuals [68].

Although our study demonstrated several major advantages of visualizing the mental health risk surface using shared and age group-specific components, further improvements are possible to improve the findings. First, as mentioned earlier, the mental health disorder dataset that we have utilized comprised an aggregate of different sub-types of mental health disorders in Toronto. As mental health risks in young and old people may vary based on these sub-types, a more detailed pattern of mental health risks in young and old age groups could be identified if the sub-types' data become available in the future. Second, our dataset did not contain mental health disorder cases from long-term care and complex continuing care facilities during the study period. Future studies can collect and include data from these facilities to refine the risk assessment process further. Unfortunately, given the scope and objectives of the study, it was not possible for us to collect and integrate this data into our models. However, it is possible to account for the patterns missing due to the lack of data from long-term care and complex care facilities when our risk maps are studied in combination with the hotspot maps. Finally, this is an ecological study that is conducted using group-level data. Therefore, the results correspond to findings applicable to young and age groups only, and no individual-level interpretations should be drawn from the findings.

Additionally, while employing BSCSM, some careful consideration is required. First, BSCSM can be susceptible to the selection of prior distributions, and inappropriate selections may lead to biased results [28]. Therefore, a sensitivity test using different sets of hyperpriors for the precision parameters is essential to finalize the priors for the precision parameters. Second, model complexity and interpretability could be an issue if the constructed model is too difficult to interpret and joint model distinguishability is

low. For example, in our BSCSM analyses, distinguishing the risk gradient of the two age groups is often challenging. We overcame this constraint by making the risk gradient of one outcome the inverse of the other outcome ($\lambda_1 = \lambda$ and $\lambda_2 = \frac{1}{\lambda}$). For more details, please see Section 2.2. Lastly, overfitting could be a constraining issue, especially if the model parameters are large relative to the analyzed data. Hence, it is important to only incorporate the parameters that are relevant to the study context and consistent with the size of the data being analyzed.

Despite the existing limitations and scope of future improvements, our study has taken up the challenge to address the complexities in modeling the latent spatial processes and risk factors governing the mental health disorder cases of young and old age groups in Toronto neighborhoods. Our findings provide critical insights into the spatial patterns of the mental health disorder risk shared by young and old age groups and the risks that are specific to young and old people. Finally, the advantage of Bayesian shared component spatial modeling with regards to non-shared component approaches was reported, which can offer a new approach for future research to study age group-specific mental health risks.

5. Conclusions

Understanding mental health disorder risks in young and old age groups can help elucidate the present and future mental health burdens in an area. However, mental health risk assessment becomes extremely challenging due to the spatially varying shared and age group-specific processes and mental health risk factors. Furthermore, advanced multivariate techniques are required to jointly model the cases of young and old mental health disorders and identify the spatially shared and age group-specific high-risk areas.

This study, using mental health disorder data for the young (20–44 years) and old (65+ years) age groups in Toronto neighborhoods, attempted to demonstrate the use of Bayesian shared component spatial modeling (BSCSM) in elucidating shared and age group-specific mental health risk patterns. The application of BSCSM allowed young and old mental health disorder cases to be studied using a single model but as two different outcomes and allowed the adjustments of unmeasured covariates and spatially varying processes, such as dependence and heterogeneity in the risk factors and observed cases. In addition, the posterior probabilities of the shared and age group-specific random effect terms were measured to identify hotspots of mental health disorders. Finally, to assess the usefulness of adopting the BSCSM approach, the mental health disorder risks for young and old age groups were assessed using the crude standardized risk ratio and Bayesian non-shared component modeling (BNSM) techniques.

The findings suggest evidence of a substantial presence of a spatially shared risk of mental health disorders and age group-specific variations in mental health disorder risks. Both the risk and hotspot maps suggest that the neighborhoods located in southcentral parts of the Toronto area had experienced elevated risks of mental health disorders in young and old age groups. However, high-risk neighborhoods for young people were located in the southern region and extended from the east to west direction in Toronto. Similarly, the hotspots of mental health disorders for the elderly group were mainly located in the north-central parts of Toronto. The results further suggest that the models from the BSCSM approach had outperformed the crude risk assessment and the non-shared component approach and provided a detailed picture of the mental health disorder risk of the two studied age groups.

Therefore, this work provided empirical evidence on how the shared and age group-specific risks spatially vary for mental health disorders of young and old age groups. The study further demonstrated an alternative to conventional risk assessment approaches, which future mental health studies can adopt to analyze multiple mental health outcomes and better understand mental health risks in an area.

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