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Invited review

Application of geospatial analysis in health research: A systematic review of methodological aspects of studies on violence against children and young people

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ABSTRACT

Background: Geographical variation exists in violence experienced by children and young people; however, there is limited research applying geospatial techniques to study this variation, and the methodological quality of this body of work is unclear.
Objective: This study aimed to review the application of geospatial analysis in research on violence against children (VAC) and evaluate how essential methodological aspects are reported.
Methods: Twelve databases were searched for studies on VAC using geospatial techniques. Two independent reviewers screened the papers for eligibility. Findings were narratively synthesised.
Results: Sixty studies were included. Six studies estimated the prevalence of VAC and 54 investigated the associations between VAC and covariates. Most studies were conducted in the US (68 %), and the broad definition of 'child maltreatment' (53 %) was the most common form of violence explored. Most studies (83 %) used administrative data, whereas 23 % used an ecological study design to estimate the associations between risk factors and official reports of VAC. Frequentist modelling approaches were used in 54 % of the studies, and 47 % investigated VAC at census tract level. Model fit metrics were reported in 69 % of studies.
Conclusions: Current knowledge of the geographical distribution of VAC is severely limited because of the reliance on administrative data, which vastly underestimates the prevalence of VAC compared with self-reports and poor reporting of quality characteristics. There is a huge opportunity for applying geospatial methods in VAC research in diverse geographic contexts. Future research must adopt rigorous and standardised approaches to model fitting and validation and make better use of self-reported data.

1. Introduction

The scourge of violence against children (VAC) continues to persist, regardless of global public health and humanitarian efforts to systematically prevent and end it. It is estimated that approximately one billion children under 18 years of age globally experience physical, sexual, or emotional violence every year (Hillis et al., 2016).

Despite global efforts to eliminate it, VAC continues to exist due to varying cultural beliefs, norms, and social practices regarding

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child-rearing in societies where parents widely support the use of physical or psychological punishment to correct children's behaviours (Akmatov, 2011; Lev-Wiesel et al., 2018). There appears to be a significant geographical disparity in the levels of VAC, for example, with some authors reporting high prevalence in low- and middle-income countries (LMICs) and moderate prevalence in high-income countries (HICs). Although the existing data are incomplete, prevalence and meta-analysis studies have estimated that the prevalence of sexual violence against girls is notably high in Australia (21.5 %), Africa (20.2 %), North America (20.1 %), Europe (13.5 %), South America (13.4 %), and Asia (11.3 %), and the rates of sexual violence among boys are more pronounced in Africa (19.3 %), South America (13.8 %), North America (8.0 %), Australia (7.5 %), Europe (5.6 %), and Asia (4.1 %) (Seff et al., 2022; Stoltenborgh et al., 2011; Stoltenborgh et al., 2015). Physical abuse is more prevalent in South America (55 %), Europe (30 %), North America (24 %), and Africa (23 %) than in Asia (16.7 %) and Australia (14 %) (Akmatov, 2011; Stoltenborgh et al., 2013). Emotional violence is highly prevalent in Africa (48 %), Asia (42 %), North America (37 %), Europe (29 %), and Australia (11 %) (Akmatov, 2011; Stoltenborgh et al., 2012). Child neglect rates appear to be higher in North America (40 %) than in Asia (30.1 %) and Europe (30.1 %) (Stoltenborgh et al., 2015). These geographic variations underscore the complex interplay between cultural, social, and contextual factors that influences the occurrence of VAC across regions.

Studies investigating the spatial distribution of VAC have primarily focused on physical, sexual, and emotional abuse and neglect, revealing complex spatial patterns influenced by diverse social and contextual factors. Evidence from studies in the United States (US) and Spain found a significant association between child maltreatment and alcohol/illicit substance use, with significant spatial clustering influenced by a range of demographic and neighbourhood attributes, such as poverty rates, immigrant concentration, and high density of alcohol-selling outlets (Freisthler et al., 2007; Marco et al., 2019). In comparison, other studies in the US and Egypt found a link between higher incidences of child maltreatment and poverty, socioeconomic disadvantages, and structural burden in neighbourhoods (Barboza-Salerno, 2020; Khatab et al., 2019). These findings highlight the severity of VAC in low-income areas and the prevalence of various social problems. Furthermore, studies have found that areas with high poverty, unemployment, and violent crime rates, as well as the association between neighbourhood factors and child abuse, have an increased risk of physical and sexual victimization (Maguire-Jack et al., 2015; Molnar et al., 2016). Spatial patterns of VAC are dynamic, with diverse manifestations clustering or overlapping in areas where high-risk factors and vulnerabilities are prevalent (Thurston et al., 2022). Evidence from the literature stresses the importance of considering contextual factors when assessing and addressing child abuse, as living in areas with high levels of physical and social disorders increases the risk of VAC.

Additionally, studies have established that sexual abuse, like other forms of VAC, exhibits distinct spatial patterns and clusters, frequently occurring in settings familiar with the perpetrators and isolated locations, as well as in neighbourhoods with elevated rates of vacant buildings, unmarried mothers, family poverty, and unemployment, as established in studies in France (Chopin & Caneppele, 2019), the US (Greeley et al., 2016), and Brazil (De Abreu et al., 2019).

It is widely acknowledged that social environmental factors, such as poverty, single-parent households, and alcohol availability, significantly contribute to the geographical occurrence of physical violence (Grogan-Kaylor et al., 2020; Thurston et al., 2022). In contrast, high concentrations of parks in some study areas are associated with increased odds of physical abuse by strangers (Bushover et al., 2020; Dong et al., 2020). Similarly, child abuse and neglect are more prevalent in neighbourhoods with high rates of teenage pregnancies, single parents, social grant recipients, dilapidated buildings, and drug-related offences (Barboza et al., 2021; Morris et al., 2019). Evidence from spatiotemporal investigations during the COVID-19 pandemic has shown shifts in VAC hotspots linked to housing burden, lack of specific assets, poverty, school absenteeism, and unemployment (Barboza et al., 2021).

Geospatial findings on emotional violence suggest that children are at risk and fear violence while travelling to school or walking in public places in the absence of an adult or caregiver (Byun & Ha, 2017; Dong et al., 2020). Furthermore, children may fear violence and become victims in areas with a high population density, small streets, small parks, and a high density of off-premises alcohol outlets (Byun & Ha, 2017; Wiebe et al., 2013). The incidence of violent victimization increased as the distance between the child's home and school increased. Hatzenbuehler et al. (2015) found that sexually bullied minority children are more likely to live in areas with a higher prevalence of hate crimes. Similarly, children who are bullied, depressed, anxious, or have low self-esteem are at a greater risk of suicidal ideation, particularly in areas where racial minorities reside (Feng et al., 2016). Thus, the complex interplay of socio-demographic, environmental, and contextual factors unveils a multifaceted perspective, necessitating nuanced strategies for intervention and prevention using a geospatial framework.

Geospatial techniques have been widely used to study and estimate the impact of various epidemiological and public health issues globally (Bergquist & Manda, 2019; Moraga, 2019). When applied to VAC research, geospatial approaches have the potential to play a significant role in identifying and describing the spatial patterns of VAC and associated risk factors in a population at a given time. Geospatial techniques rely on statistical and computational methods to analyse geo-referenced data or data relating to distance or space-time to provide more granular findings that explain and appraise the geographical distribution of VAC, which is essential for formulating informed interventions and prevention methods in resource-limited settings (Bergquist & Manda, 2019).

In VAC research, geospatial analysis techniques are used to produce maps essential for identifying spatial patterns that may be hidden in traditional statistical tables and models (Bergquist & Manda, 2019). These techniques are also helpful in forecasting VAC progression and identifying areas of high and low prevalence. In addition, findings from geospatial studies can help redirect intervention programs and resources to areas where VAC is more likely to occur. Other applications include identifying risk factors that may promote or hinder the spread of VAC, identifying changes in VAC spatial patterns over time, detecting high-risk areas for effective intervention, identifying geographical areas lacking attention in data collection, and encouraging data collection in such areas to fill gaps.

To our knowledge, no study has systematically examined and evaluated the application and methodological aspects of geospatial analysis in VAC studies. Therefore, it is necessary to review the use of geospatial analyses in VAC research. This review is essential to

Table 1
Summary characteristics of reviewed studies.

	All studies	Forms of violence against children					
		Maltreatment	Sexual	Physical	Neglect	Emotional	Other forms
All studies	60	33	5	5	4	2	11
Year of publication							
Before 1989	1	1	0	0	0	0	0
1990–1999	1	0	0	0	1	0	0
2000–2009	10	9	0	0	0	0	1
2010–2019	30	13	4	1	2	2	8
2020–2022	18	10	1	4	1	0	2
Coverage							
Sub-National	53	31	4	4	2	2	10
National	7	2	1	1	2	0	1
Countries							
USA	41	25	2	3	4	1	6
Brazil	4	0	2	1	0	0	1
Canada	4	2	0	0	0	1	1
Ecuador	1	0	0	1	0	0	0
Egypt	2	1	0	0	0	0	1
UK	2	1	0	0	0	0	1
France	1	0	1	0	0	0	0
Israel	1	1	0	0	0	0	0
South Korea	1	0	0	0	0	0	1
Spain	3	3	0	0	0	0	0
Broad purpose of the study							
Assessing changes over time and space with neighbourhood-level covariates	18	11	2	2	2	0	1
Association with individual-level covariates	8	2	0	1	0	1	3
Examining spatial patterns	6	2	1	0	2	0	1
Predicting spatial patterns with neighbourhood-level covariates	1	1	0	0	0	0	0
Relationship with neighbourhood-level covariates	27	17	2	2	0	0	6
Study design							
Ecological study	23	17	2	1	1	0	2
Cross-sectional study	10	5	1	1	1	1	1
Longitudinal study	5	3	0	1	1	0	0
Other study designs	7	2	0	1	0	0	4
Not reported	14	6	2	1	1	1	3
Data sources							
Administrative data	50	31	5	4	4	0	7
Other data sources (surveys)	10	2	0	1	0	2	4
Study variables classifications							
Socioeconomic factors	47	29	2	4	3	1	8
Demographic factors	31	17	2	2	3	1	6
Interpersonal factors	11	2	2	0	1	1	5
Psychological factors	4	1	1	0	0	1	1
Family and household factors	24	15	2	2	2	0	3
Social environment factors	48	29	3	4	2	2	8
Access to support & services	13	8	1	0	0	1	3
Not provided	4	2	1	1	0	0	0
Modelling techniques							
Bayesian - INLA	7	5	0	2	0	0	0
Bayesian - MCMC	12	8	0	0	1	1	2
Generalised Linear Models	12	3	2	1	1	1	4
Global Moran's *I*	21	14	2	0	1	0	4
Getis-Ord *Gi** statistic	4	1	1	1	0	0	1
Local Moran's *I*	4	2	1	0	1	0	0

(*continued on next page*)

Table 1 (*continued*)

	All studies	Forms of violence against children					
		Maltreatment	Sexual	Physical	Neglect	Emotional	Other forms
Spatial regression	17	14	0	2	0	1	0
Spatial scan statistics	9	0	2	2	1	0	4
Other techniques	13	2	5	2	1	0	3
Model validation							
Cross validation	3	2	1	0	0	0	0
K-fold cross-validation	2	2	0	0	0	0	0
Gelman-Rubin diagnostic plot	5	3	0	0	1	1	0
Not reported	44	24	4	5	2	1	8
Model fit metrics							
DIC	11	9	0	0	1	1	0
AIC	4	4	0	0	0	0	0
Convergence diagnosis R-hat	4	4	0	0	0	0	0
BIC	3	0	1	1	0	0	1
R-squared	3	2	0	0	0	0	1
Other metrics	28	18	0	2	2	1	5
Not reported	17	6	0	2	2	0	7
Resolution							
Census tract	28	21	0	3	2	1	1
Census block	5	3	0	1	0	0	1
street segments	5	0	1	0	0	1	3
County	3	2	0	0	1	0	0
Other resolutions	16	7	3	1	0	0	5
Not specified	3	0	1	0	1	0	1
Temporal outcomes							
Yes	18	12	2	2	1	0	1
No	21	7	2	2	3	1	6

Abbreviations: INLA = Integrated Nested Laplace Approximation; MCMC = Markov chain Monte Carlo; DIC = Deviance Information Criterion; AIC = Akaike information criterion; BIC = Bayesian information criterion.

identify the present methodologies used, their strengths, and weaknesses, and to help appraise and advance future studies. This review aims to explore how geospatial analysis methods are applied in VAC research and appraise the reporting of critical methodological aspects of geospatial analysis in VAC studies. By doing so, we hope to provide a better understanding of the current state of geospatial analysis in VAC research and identify areas for future improvement.

2. Methods

2.1. Eligibility criteria

A child is considered a person below 18 years of age (UN, 1989). However, we expanded the definition for our review to include young adults, i.e., persons aged 19 to 24 years (Sawyer et al., 2018). Thus, we operationalised the notion of "children" as those aged 0 to 24 years. We defined forms of VAC using terminologies from UNICEF (2014).

The review included geospatial analysis studies focusing on several forms of VAC, including physical, emotional, neglect, exploitation, and sexual violence, for children aged 0 to 24 years. We assessed all observational studies (cross-sectional, cohort, descriptive, and ecological). Papers published in English worldwide from the earliest available study until 08 November 2022 were included. Only published quantitative and peer-reviewed studies were considered. The eligibility criteria were applied to all retrieved studies.

2.2. Exclusion criteria

We excluded case reports, case series, experimental studies, qualitative studies, studies that described the geographical distribution of VAC without using geospatial analysis techniques, systematic reviews, non-English studies, meta-analyses, protocols, and conference abstracts.

2.3. Search strategy

We conducted a systematic search of relevant studies in OVID (MEDLINE, APA PsychINFO, EMBASE, Global Health, and Social Policy and Practice), Web of Science (Core Collection, SciELO, and KCI-Korean), SCOPUS, and EBSCOHost (Academic Search Complete, CINAHL Complete, and Open Dissertations). Cochrane systematic reviews and PROSPERO databases were searched to identify if similar reviews existed. The databases were searched by T.W.S. from the earliest available publication to 08 November 2022.

We developed a thorough search strategy for MEDLINE and adapted it for other databases. The key search phrases were derived from Cerna-Turoff et al. (2021) and Manda et al. (2020). Appendix A contains the complete key search phrases using the Boolean operators. Search phrases were matched against records published in selected databases' titles, abstracts, and medical subject headings (MeSH) terms (where applicable). The protocol for the systematic review was registered in the OSF registry (registration DOI:10.17605/OSF.IO/Q5C2S).

2.4. Study selection process

The articles obtained from our search were exported to EndNote X8 reference manager for compilation and screening. In the first screening stage, EndNote X8 was used to detect and delete duplicates from the library. Subsequently, the abstracts and titles of all remaining records were manually screened to determine if they met the eligibility criteria. Next, T.W.S. and S.S. independently screened full texts of all eligible articles for further inclusion in the review. The final number of studies included in the review was decided by consensus with K.D. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram in Fig. 2 illustrates the screening and selection process for selected studies.

2.5. Data extraction

We prepared a standard Microsoft Excel spreadsheet to extract data required from selected papers. Data extracted included the year of publication, study outcomes, study design, data source used, explanatory variables, resolution, and geospatial analysis techniques applied. T.W.S. extracted all relevant data from selected studies and discussed the results with S.S. and K.D. Key summary data extracted from the selected studies are listed in Table 1, and additional data are provided in Appendix A.

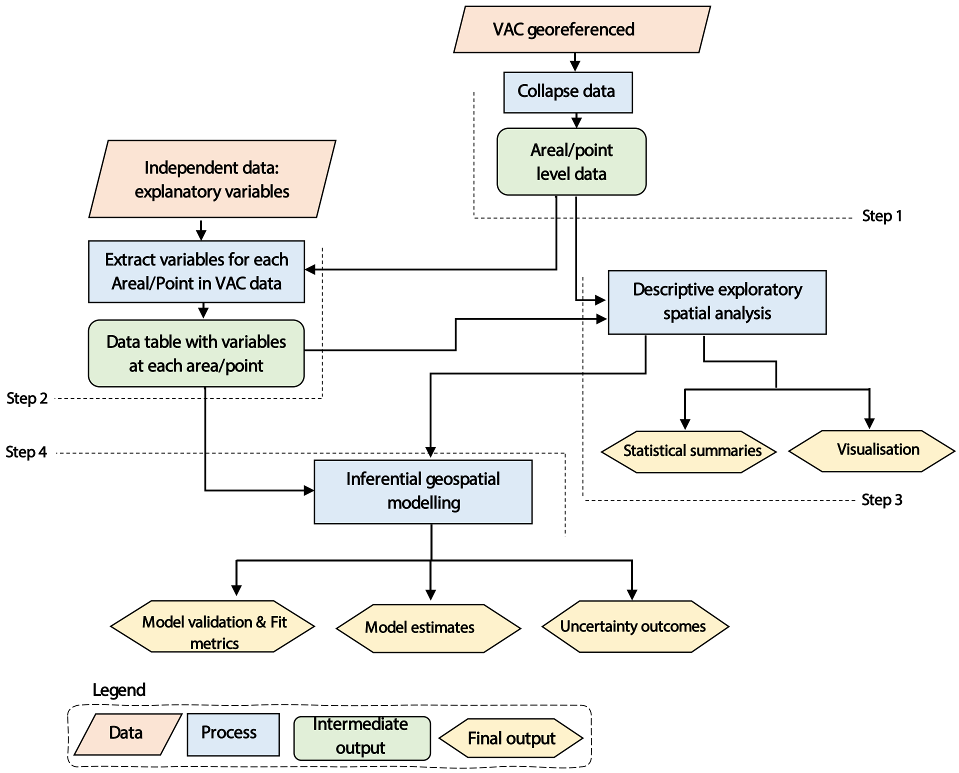

Fig. 1. Overview of geospatial analysis process adopted from Mayala et al. (2019).

2.6. Quality of studies and geospatial modelling framework

This review discusses the quality of studies using a standard geospatial modelling framework, as depicted in Fig. 1. The primary purpose of using this framework in our review was to assess the quality and robustness of the selected articles rather than being used as part of the inclusion criteria. The geospatial modelling framework is a valuable tool for evaluating two different types of geospatial studies: (1) descriptive exploratory studies that evaluate the prevalence of VAC within specific geographical areas by providing insight into the distribution and magnitude of VAC, and (2) geospatial modelling studies that estimate the association between VAC and various risk factors, enabling us to identify potential determinants and VAC risk factors associated with different geographical areas.

The geospatial analysis process involves using software with GIS capabilities in the following steps (Mayala et al., 2019):

- **Step 1:** Summarise self-reported data or aggregate reported incidents of VAC by geographical area to the desired spatial resolution, such as census tracts, blocks, states, or other relevant resolutions, to preserve location-based information.
- **Step 2:** For modelling studies, if the data in Step 1 lack explanatory variables, extract explanatory variables from independent sources (e.g., household surveys, census) and join them with the areal/point-level data in Step 1 to create a single spatial file.
- **Step 3:** Perform descriptive exploratory spatial analysis of the data collected in Step 1 or Step 2 to uncover spatial patterns, detect errors, and select suitable geospatial models for the data. Descriptive exploratory studies that estimate VAC prevalence will end at this stage by providing statistical summaries and visualisations.
- **Step 4:** To ensure accurate estimates, geospatial models are constructed by minimising prediction errors, biases, and overfitting that may arise from the data. It is vital to present the decisions made throughout the process clearly and logically to allow readers to evaluate the reliability of estimates (Ferreira et al., 2020). The specific geospatial modelling techniques used depend on the research questions, properties of the dependent variable, and identified spatial patterns in Step 3. These techniques aim to test hypotheses and associations and predict outcomes using one or more explanatory variables at different locations. The outputs included model validation, fit metrics, model results, and uncertainty outcomes.

Drawing from the framework outlined in Fig. 1, we evaluated key aspects presented in selected studies at various stages of geospatial analysis by synthesising how studies report vital methodological aspects for their interpretations. Additionally, we appraised

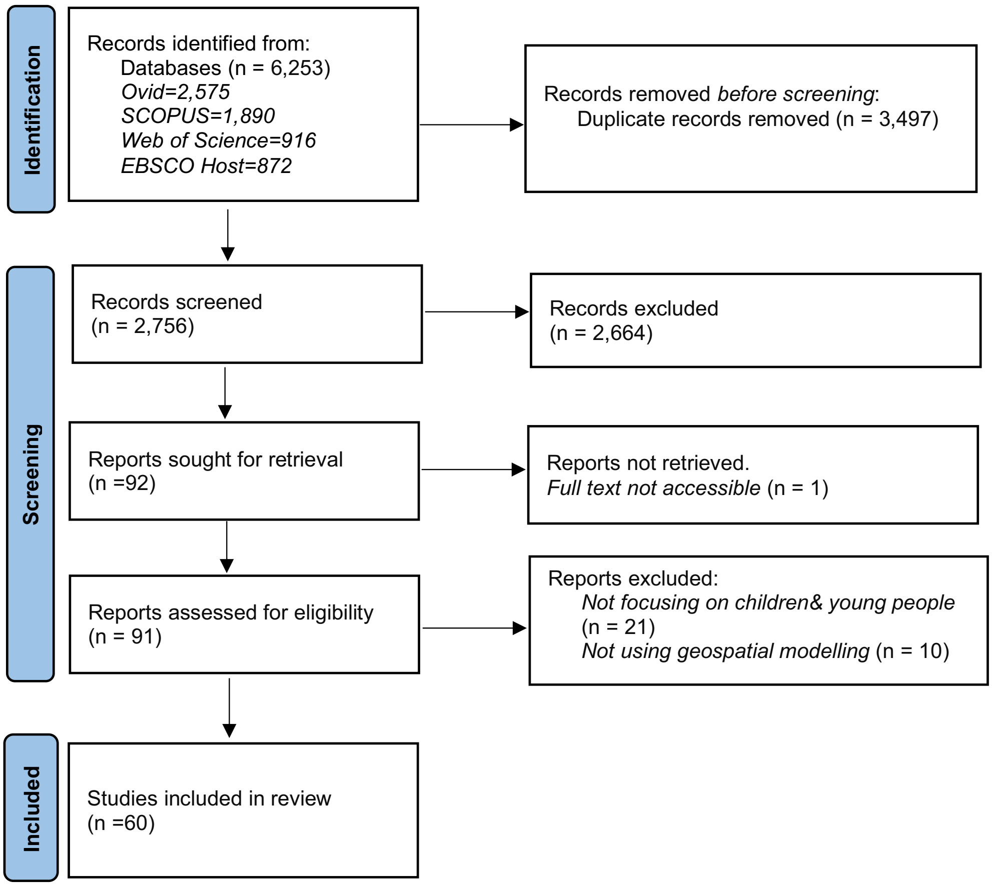

Fig. 2. PRISMA flowchart of the article selection process.

the quality of the studies based on the study designs employed by researchers to address research questions within the geospatial modelling framework. Study design refers to specific methods and approaches used to collect and analyse data in a study (Ranganathan & Aggarwal, 2018). This involved examining different study design methods, such as cross-sectional (data collected from individuals at the same point in time), ecological (data collected from groups or populations at a single point in time), cohort (data collected from the same individuals over an extended period), and other study designs.

2.7. Data synthesis and reporting

We provide a table summarising the review's main findings and narrative synthesis guided by the geospatial modelling framework to address the review's objectives. However, meta-analysis was not the goal of this review. We followed the PRISMA guidelines provided in Appendix A to report our review findings (Page et al., 2021).

3. Results

3.1. Study selection

The search initially yielded 6253 studies, of which 3497 were duplicates and deleted from the EndNote X8 library. The remaining 2756 studies were manually screened based on their abstracts and titles to assess their eligibility for inclusion. Of these studies, 2664 did not meet the selection criteria, and the remaining 92 were further screened by reading the full texts. Unfortunately, the full text of one article could not be retrieved due to limited access. After reviewing the full texts, we excluded 21 studies that did not focus on children and young adults, and the remaining 10 articles were excluded for not using geospatial analysis. Ultimately, 60 studies were included in this review (Fig. 2).

3.2. Characteristics of selected studies

Table 1 shows that the first study identified in this review was published in 1988, followed by 11 studies conducted between 1994 and 2009. The number of studies increased progressively, reaching a peak of 30 studies conducted between 2010 and 2019 (Appendix A, Fig. 1). Most of the studies (53) were conducted at the sub-national level. The majority of studies (41) were conducted in the US, and the remaining 19 were conducted in Brazil, Canada, Spain, the United Kingdom (UK), Egypt, France, Ecuador, Israel, and South Korea (Table 1).

3.3. Methodological aspects of VAC studies

3.3.1. Study design

The current review found that the selected studies employed both descriptive and inferential geospatial approaches, as outlined in Fig. 1. Of the 60 studies reviewed, six focused on estimating the prevalence of VAC (i.e., ended at stage 3 of the modelling framework), whereas 54 examined the association between VAC and other variables. Table 1 shows that the broad purpose of descriptive studies was to investigate the spatial patterns of VAC found in six studies. The findings further show that most inferential studies (27) aimed to explore the relationship between different forms of VAC and neighbourhood-level risk factors, whereas 18 studies examined the spatiotemporal distribution of various forms of VAC. Furthermore, eight studies investigated the association between different forms of VAC and individual-level characteristics, and one study aimed to predict the spatial patterns of child maltreatment (Appendix A).

Regarding studies that aimed to determine the prevalence of VAC, two used a cross-sectional design, one employed a retrospective cohort design, and three did not specify their study designs. As for the 54 studies that estimated associations and spatiotemporal patterns, 23 used an ecological design, 10 used a cross-sectional design, and five employed a longitudinal design. Additionally, 13 studies did not report the study design used in their research (Table 1).

3.3.2. Data sources

Table 1 shows that administrative data (50) was the most widely used data source to investigate VAC in a geospatial context, followed by other data sources (student health surveys (5), Demographic Health Surveys (2), other household surveys (2), and clinical surveys (1)).

3.3.3. Analysis and modelling techniques

Table 1 shows that 29 of the 60 studies used at least one spatial autocorrelation or clustering method to examine and quantify non-random similarities or dissimilarities in the spatial patterns across the study areas. The most used measures to detect spatial autocorrelation are the *Global* Moran's *I* statistic (21), followed by the *Local* Moran's *I* statistic (4), and the Getis-Ord *Gi** statistic (4). The *Global* Moran's *I* statistic is helpful in evaluating overall spatial autocorrelation in a study area but may limit the understanding of the prevalence of VAC in specific local contexts (Fortina & Dale, 2009). The *Local* Moran's *I* statistic helps identify both local hotspots and coldspots of VAC and outliers (high-prevalence areas with low-prevalence neighbours and low-prevalence areas with high-prevalence neighbours) at specified distances. The Getis-Ord *Gi** statistic identifies hotspots and coldspots by considering all the data values in the calculations (Getis, 2010).

Table 1 shows that spatial regression techniques, such as ordinary least squares (OLS), geographically weighted regression (GWR), and generalised least squares (GLS), were the most commonly used methods for examining the relationship between VAC and associated risk factors using areal data in geospatial modelling studies published between 2000 and 2014, with 17 studies using these methods. These methods aim to provide accurate estimates of the prevalence and burden of VAC by capturing the associations between various forms of VAC and one or more explanatory variables. Additionally, 12 studies published between 2010 and 2022 employed generalised linear models (GLMs), which accommodate a wide range of data distributions for continuous and categorical variables by relying on a link function to relate the response variable to linear combinations of explanatory variables. Conversely, we found that the Bayesian-MCMC and Bayesian-INLA models were used in 12 and 7 studies, respectively. Bayesian models are hierarchical models that generate posterior distributions for model parameters using either Markov Chain Monte Carlo (MCMC) simulations or Integrated Nested Laplace Approximations (INLA) (Gelman et al., 2013). Owing to advances in computing power, the trend in reviewed studies shows that Bayesian models are becoming the preferred modelling techniques in VAC studies, with more than three-quarters of the studies published in the past five years using Bayesian approaches, surpassing frequentist geospatial analysis methods. Additionally, this advancement has led to the INLA method outperforming MCMC simulations in terms of speed and precision, making it a popular alternative Bayesian modelling technique owing to its lower complexity and ability to overcome the problem of sample convergence and mixing (Ferreira et al., 2020; Manda et al., 2020).

In studies using point data, Table 1 shows that spline interpolation, inverse distance weighting, point density analysis, empirical Bayesian Kriging, and kernel density estimation were used in addition to multilevel spatial models to derive VAC estimates by interpolating between known data points to produce forecasts in geographical areas with missing data (see Appendix A). Furthermore, non-parametric statistical methods were used to provide estimates for the distribution-free data.

This review highlights the evolution of the application of geospatial analysis methods in VAC research over the past 34 years. The findings demonstrate how studies have shifted from relying on frequentist statistical approaches, such as classical linear regression models, OLS, GLMs, and non-parametric tests, which fail to account for spatial autocorrelation present in the data and do not leverage information from neighbouring areas. Most recent studies seem to apply more robust modelling methods, such as spatial regression models and hierarchical Bayesian models, which have gained popularity because they are well-suited to model spatial data.

3.3.4. *Explanatory variables*

In this review, we distinguished between six studies that aimed to estimate VAC prevalence and 54 studies that looked at VAC association with other variables. We limited the interpretations of the findings in Subsections 3.3.4 and 3.3.5 to 54 studies that investigated the association between VAC and different risk factors, as well as those that examined the spatiotemporal distribution of various forms of VAC.

We classified the risk factors identified in evaluated studies into seven groupings that closely resemble the dimension of the social-ecological framework for understanding and preventing VAC, namely demographic, socioeconomic, environmental, psychological, and interpersonal attributes, and social support services. Covariates related to social environment were the most commonly used explanatory variables to describe the geographical distribution of VAC, as reported in 48 studies, followed by socioeconomic attributes (47), family and household characteristics (24), demographics (31), access to support and services (13), interpersonal attributes (11), and psychological factors (4) (Table 1). However, four modelling studies failed to account for the variables used in their analyses.

3.3.5. *Model validation and fit metrics*

In our review, we noted that studies interchangeably used the terms model 'validation' and 'selection', i.e., studies described the model selection technique as a strategy for validating fitted models. We found that 44 of 54 studies did not describe the model validation methodologies employed in their investigation. Table 1 shows that the Gelman-Rubin diagnostic plot (5) was the most used model validation method in the ten studies reporting model validation, followed by cross-validation (3) and K-fold cross-validation (2). Although more than three-quarters of the studies did not account for model validation, 37 of the 54 studies reported multiple model fit metrics to examine the validity of model predictions, as shown in Table 1. However, 17 studies did not publish the model-fit criteria used to assess the quality of the fitted models. Despite these shortcomings, there has been discernible improvement in the reporting of model validation and fit metrics in recent years, particularly in publications from the late-2000s to 2022.

3.3.6. *Resolution*

Table 1 shows that most studies have investigated VAC at the census tract level (28), followed by census blocks, street segments, and counties. Other resolutions were used in 16 studies. However, three studies failed to disclose the geographical resolution used in their analyses. Although diverse spatial resolutions were employed, the trend indicated a preference for smaller geographic units, such as census blocks, street segments, and census tracts, as opposed to larger areas, such as districts, counties, regions, electoral wards, zip codes, and postcodes. This shift has become particularly noticeable in recent studies.

3.3.7. *Spatiotemporal outcomes*

Although 39 studies utilised space-time data to generate estimates, Table 1 shows that only 18 of the reviewed studies provided spatiotemporal analysis findings, whereas the remaining 21 failed to perform spatiotemporal analysis.

3.4. *Forms of VAC*

Fifteen forms of VAC were investigated across the reviewed studies using geospatial analysis. We divided the forms into six distinct groups based on their similarities. The groupings were child maltreatment; sexual, physical, and emotional abuse; neglect; and other forms of VAC. Table 1 highlights the specificities of each form of violence based on study characteristics.

3.4.1. Child maltreatment, sexual, physical, and emotional abuse, and neglect

Child maltreatment studies may be considered pioneers in geospatial analysis within the field of VAC, with 33 of the 60 studies reviewed focusing on this topic. The first geospatial study on child maltreatment was published in 1988, followed by one study on neglect in 1994, and 12 studies on maltreatment published between 2000 and 2015. With the widespread availability of GIS tools and geostatistical methods since 2000, it took approximately 15 years for other forms of VAC to be studied geospatially. Table 1 illustrates that most child maltreatment studies (32) were conducted in HICs (the US, Canada, Israel, and Spain), with only one study conducted in LMICs (Egypt). These studies primarily focused on examining the reporting of child maltreatment patterns and associated risk factors using administrative data. Notably, it was not until 2017 that self-reported data (i.e., data collected from children) were utilised to investigate the prevalence of child maltreatment geospatially. In contrast, geospatial studies on sexual abuse began relatively recently, with all the reviewed studies published since 2015. These studies were conducted using administrative data collected in the US, Brazil, and France. However, no geospatial studies have used self-reported data to explore the prevalence of sexual abuse in children.

Physical abuse has been examined geospatially in the US, Brazil, and Ecuador. Between 2018 and 2022, four studies investigated the reporting of physical abuse incidents among children using administrative data and only one study used self-reported data to investigate the prevalence of physical abuse in 2020. Regarding emotional abuse, geospatial patterns were examined in the US and Canada, using self-reported data from 2013 and 2016. However, geographical patterns of child neglect were explored solely in the US using administrative data, and none of the studies used self-reported data for this purpose (Table 1).

3.4.2. Other forms of VAC

Geospatial methods for producing estimates for small areas have generated estimates for different forms of VAC. We identified studies on violent injuries (3), crime (3), homicides (2), child labour (1), victimization (1), and bullying (1), as shown in Table 1. Overall, seven studies focused on investigating the geographical patterns of other forms of VAC using administrative data, whereas only four studies investigated the prevalence of other forms of VAC using self-reported data (Table 1).

4. Discussion

4.1. Summary of main findings

To our knowledge, this is the first systematic review to describe the methodological aspects of geospatial analysis in VAC research. More than 70 % of studies in the field have been published since 2015, focusing strongly on HICs such as the US, UK, Canada, Spain, and France. However, LMICs have not received much attention in geospatial VAC research. Reports of child maltreatment from official administrative data are by far the most investigated form of violence, which is highly problematic, as official records may vastly underestimate the prevalence of violence compared to children's self-reported data. Furthermore, distinct studies on physical, sexual, and emotional abuse and neglect have received little attention.

We observed that the quality of the reviewed studies varied, with several notable gaps accounting for the study design and spatial dependence. Additionally, the model fit and validation metrics are often inadequately reported. At the same time, geospatial resolution and spatiotemporal analysis were inconsistently applied. The explanatory variables used in the studies were sourced from independent secondary datasets aggregated at different geographical levels, which made it difficult for researchers to determine the individual-level characteristics that shaped the geographical distribution of VAC. These findings highlight the need for more rigorous and standardised approaches in VAC geospatial research that focus on diverse geographic contexts and use children's self-reported data sources.

4.2. Discussion of main points

Evidence from literature suggests that the prevalence of VAC is a significant issue in both LMICs and HICs (Akmatov, 2011; Al-Khatib, 2022). However, the number of studies addressing the geographical distribution of VAC in LMICs remains limited, and there is a paucity of international and intercontinental geospatial studies, particularly in regions with high rates of VAC, such as Asia, South America, and Africa. These regions present unique challenges influenced by factors such as economic uncertainty, political instability, and cultural beliefs, which may affect the occurrence of VAC. Therefore, exploring the geospatial nature of VAC in LMICs at both the international and intercontinental levels would be beneficial in identifying areas of varying prevalence rates and detecting specific demographic, geographical, and other attributes that expose children to the risk of violence. This information will help local and international organisations to combat VAC by allocating resources to severely affected areas.

Based on our findings, administrative data have emerged as the dominant source in geospatial research on VAC. The predominance of this source can be attributed to the high concentration of reviewed studies (over 68 %) conducted in the US, where researchers have relied on data collected by various child protection agencies. Administrative data provide valuable information on child maltreatment which compensates for the lack of access to consistent and complete data on self-reported VAC. However, the use of administrative data presents numerous challenges and limitations, which have been extensively discussed in VAC literature (Coulton et al., 2007; Jud et al., 2016; Thurston et al., 2017). In the world of violence research, using this data source to measure prevalence is not widely considered a good source because, in essence, these studies measure the reporting of violence, which depends on the prevalence, willingness to report, and availability of places to report.

In this review, we noted several challenges associated with using administrative data to produce geospatial estimates of VAC. First, data collected from administrative records do not conform to sample design, suggesting that the observed spatial patterns are not random (Jud et al., 2016). This lack of randomness may undermine the representativeness of the data and raise concerns regarding the generalisability of the findings. Second, the concentration of data collection in low-income areas creates a biased picture of VAC prevalence, as this may fail to capture incidents occurring in neighbourhoods with different socioeconomic statuses. Third, when used in modelling studies, data often lack individual- and household-level factors that are crucial for understanding children's exposure to violence (Anwar et al., 2020). Without these contextual variables, the analysis may overlook the significant contributors to VAC in a spatial context. Additionally, the ambiguity surrounding what is included as abuse (substantiated or unsubstantiated cases) further complicates the estimation process and may lead to inconsistencies in prevalence estimates (Al-Khatib, 2022; Thurston et al., 2017).

Moreover, data collected from administrative sources rarely refer to specific neighbourhoods, making it challenging to analyse geospatial patterns at the desired spatial scale. Similarly, the primary purpose of collecting these data is not to estimate VAC prevalence, thus resulting in a limited collection of demographic and individual characteristics. This limitation restricts a comprehensive understanding of VAC and hinders the identification of specific risk factors associated with different forms of VAC (Farrar et al., 2020). Furthermore, the underreporting of incidents and the difficulty in distinguishing between multiple forms of violence within the data may further compromise the accuracy of prevalence estimates and trends. Another notable limitation is the possibility of increased reporting of VAC incidents in urban areas compared to rural areas, which could lead to a biased understanding of the spatial distribution of VAC (Jud et al., 2016). This bias may lead to an incomplete and distorted understanding of the incidence of VAC, particularly in rural and remote regions, where incidents are underreported or less visible.

Considering these challenges, researchers must acknowledge the limitations of using administrative data and exercise caution when interpreting their findings. To overcome these drawbacks, it will be beneficial for future studies to explore alternative data sources that provide more comprehensive and representative information on VAC, such as children's self-reported data. This approach will not only improve the accuracy and validity of research, but it might also lead to a more nuanced understanding of VAC's spatial distribution and determinants of VAC. Studies, such as those by Khatab et al. (2019), Samak (2017), Dong et al. (2020), Bushover et al. (2020), and Hatzenbuehler et al. (2015) used self-reported survey data to estimate the prevalence of VAC and employed methodological approaches that addressed the limitations associated with administrative data. However, for some age groups, such as infants, toddlers, and young children, proxy reports are necessary, as children may be unable to report their own experiences and may also lack the ability to accurately recall past events (Jud et al., 2016; Lev-Wiesel et al., 2018). Additionally, it is worth noting that systematic collection of self-reported data is a resource-intensive process.

The heavy reliance on administrative data in the reviewed studies may have resulted in the predominant use of the ecological study design. However, this design has several limitations, including ecological fallacy, modifiable areal unit problem, misaligned data problem, and confounding factors, as highlighted by the limitations of the reviewed studies (Barboza, 2019; Bernardino et al., 2019; Greeley et al., 2016). The aggregation of data at the group level prevents the interpretation and evaluation of VAC incidents at the individual level and the identification of individual-level risk factors associated with VAC. As a result, causality between VAC forms and relevant individual-level risk factors could not be conclusively established in most reviewed studies that examined the association of VAC with covariates. It will benefit future studies to document their study designs and consider using cross-sectional, cohort, or longitudinal designs to improve the quality and transparency of geospatial analyses of VAC.

Our review highlights that child maltreatment has received significant attention in geospatial studies, underscoring its global prevalence and severity. However, treating different forms of VAC as aggregated measures in geospatial analysis may often yield incorrect spatial patterns because of the distinct spatial distribution of each form of violence, as some forms of violence tend to cluster in certain geographical regions than in others (Lev-Wiesel et al., 2018; Thurston et al., 2017). Thus, combining different forms of violence into a single form of VAC (maltreatment) impedes the identification of unique spatial patterns of individual forms of VAC and the risk factors associated with different neighbourhoods (Paulsen, 2004). Therefore, relying on combined measures could limit our understanding of the spatial distribution of the distinct forms of VAC. In line with the recommendations of Thurston et al. (2017), we reiterate that future geospatial studies using larger datasets consisting of multiple forms of violence must separately investigate different forms of VAC, their causes, and diverse spatial patterns. In addition, more work is required to evaluate whether the modelling choice selected by researchers influences the geographical distribution of VAC forms and their associated risk factors. This approach is likely to provide a more comprehensive understanding of the spatial dynamics of VAC and to inform targeted interventions and policies in highly affected areas. Therefore, by focusing on specific forms, researchers can gain insight into the unique challenges and needs of different areas, thereby enabling the development of effective strategies to prevent and reduce VAC.

For studies that explore the association between VAC and various risk factors, it is essential to report the explanatory variables used to explain spatial distribution patterns. However, our review found that 7 % of studies failed to report the covariates used in their analyses. Most studies have focused on examining the spatial patterns of VAC by considering variables related to the social environment, socioeconomic status, demographics, family and household attributes, and access to support and services. Nevertheless, there is a noticeable gap in examining the role of psychological and interpersonal factors, as well as other individual characteristics. The emphasis on neighbourhood-level determinants over individual-level characteristics may be due to the prevalent use of ecological study design and administrative data, as well as reliance on independent secondary data sources, which makes it challenging to obtain and quantify attributes from individuals at risk of abuse. This limitation inhibits our knowledge of the individual-level risk factors that explain the geographical distribution of VAC.

Although current studies present limited knowledge of individual-level risk factors, they have provided evidence of risk factors at the neighbourhood level that may help identify geographical areas severely impacted by VAC. These findings may be helpful in identifying areas for further research aimed at studying the individual-level risk factors that expose children to violence. To address the gap in the use of individual-level risk factors, future studies must aim to quantify the relationship between the geospatial patterns of VAC and individual-level characteristics. This will provide valuable insights into how individual-level factors contribute to the spatial distribution of VAC. Considering a broader range of covariates and utilising more comprehensive data collection methods has the potential to expand our understanding of the complex spatial dynamics underlying the geography of VAC.

The choice of modelling techniques in geospatial analysis is essential for obtaining accurate and robust results. Most studies have traditionally relied on frequentist modelling and conventional descriptive statistics, which do not permit the incorporation of prior knowledge of VAC. Our review noted a recent increase in the use of Bayesian hierarchical models in VAC research. These models offer precise estimations, account for temporal and spatial structures, handle overdispersion and missing data, and incorporate prior knowledge of VAC into the analysis (Freisthler & Kranich, 2022; Thurston et al., 2022). As a result, Bayesian hierarchical models have the potential to become the preferred modelling technique in VAC studies, although the field is still evolving. These models will enable researchers to obtain more accurate and comprehensive insights into the spatial dynamics of VAC by incorporating prior knowledge from non-geospatial VAC studies.

Fitting geospatial models requires researchers to ascertain that statistical performance standards are met at each stage. The assessment and reporting of model assumptions, precision, completeness, and validity are essential (Bergquist & Manda, 2019). Unfortunately, a substantial number of studies in our review (45 of 54) did not provide transparent and credible model validation metrics. This lack of transparency may raise concerns about the eligibility and validity of fitted models, particularly for studies employing sophisticated techniques such as multilevel and Bayesian models. Comprehensive assessments of the model fit and performance are fundamental for ensuring the accuracy and trustworthiness of the results. Thus, addressing these validation issues will improve clarity and rigour in reporting model validation, which could lead to improvements in geospatial techniques in VAC studies.

Our review findings also shed light on the significance of the data granularity. We observed that the choice of dataset influenced the level of granularity and aggregation methods employed in the studies. Notably, most of the studies in the review relied on census tract-level resolution, representing a larger geographical scale than finer resolutions such as census blocks or street segments. However, it is essential to note that VAC estimates derived at broader scales, such as census tracts or postcodes, may be inaccurate, leading to different interpretations. This is because in the analysis, areas with smaller populations of children may be assigned equal weights as areas with larger populations of children, resulting in distorted spatial patterns of the prevalence of VAC (i.e., nearby areas will tend to be more spatially correlated compared to areas further away) (Freisthler et al., 2005). Furthermore, it is essential to acknowledge that higher geographical levels, such as census tracts, do not inherently correspond to well-defined neighbourhoods (Freisthler et al., 2007).

There are also ethical considerations linked to data granularity in self-reported surveys, in which geographical information can potentially be used to identify participants. To anonymise 'place', geo-points are often masked using various methods, such as displacing them by a radius of 2 km in urban and 10 km in rural areas or masking them to the centroid in case of areal data (Burgert et al., 2013). Researchers who plan to collect primary data from children must also spatially anonymise the location variables in their data to protect children's identities.

Therefore, researchers must carefully consider selecting an appropriate resolution to obtain precise and meaningful estimates and interpretations of rates across different spatial resolutions while protecting participant anonymity. When estimating the spatial distribution of VAC using self-reported data, it may be beneficial for researchers to analyse the data at the enumeration area level or use geo-coordinates to provide more precise geospatial estimates and to identify areas affected by VAC.

This review noted the scant application of spatiotemporal analysis to detect changes in the spatial distribution patterns of VAC prevalence. This limits our understanding of the effectiveness of the different interventions and preventive strategies implemented in various geographical areas. We noted that the limitation in spatiotemporal analysis may be due to challenges related to data availability, as most researchers rely on the use of administrative data and data from cross-sectional surveys. As the field advances and more space-time data on VAC become available, it will be beneficial for future studies to incorporate spatiotemporal analysis to improve our knowledge of the development and evolution of VAC clusters. This approach will enable studies to capture the changes in the spatial patterns of VAC prevalence over time, identify emerging hotspots, and acquire valuable insights for targeting interventions and prevention strategies. Thus, incorporating spatiotemporal analysis could enhance our ability to detect temporal trends, assess the effectiveness of interventions, and contribute to more informed decision making in combating VAC.

4.3. Strengths and limitations

This paper offers a comprehensive overview of the application of geospatial analysis in VAC research, covering 34 years of research investigating different forms of VAC. Our review demonstrates the extensive application of various exploratory spatial analyses and conventional spatial modelling techniques in VAC studies. Despite the strengths of this review, this study has some limitations. First, our search terms may have omitted some geospatial studies on VAC as GIS terminologies are continuously evolving. Second, we limited our search to studies indexed in OVID, Web of Science, SCOPUS, and EBSCOhost databases until 08 November 2022. Therefore, it is possible that we may have missed relevant studies published in other databases or after our search date. Finally, we excluded non-English studies, and grey literature was not searched.

4.4. Implications for future studies

To overcome the drawbacks associated with using administrative data and accurately measuring the geographical distribution of VAC, future research must consider leveraging survey data collected from children through various sources, such as multiple indicator surveys (MICS), health behaviours in school-aged children, demographic health surveys (DHS), global school-based health surveys, and violence against children surveys (VACS). These surveys provide comprehensive and rigorous information on various forms of violence and health-related outcomes that may enable more accurate population-level estimates. However, it is essential to note that additional geo-processing might be required to effectively incorporate these survey data into geospatial analysis, as they are often not conducted in well-defined geographical boundaries and may lack the necessary geometry. In particular, the VACS, MICS, and DHS datasets contain geo-referenced data at enumeration area level, which is desirable for geospatial analysis. However, access to geographic location attributes may require the consent of relevant national government authorities, and there are important ethical considerations in place to prevent participant identification. By leveraging these survey datasets and addressing the challenges of geospatial analysis, future studies can improve our knowledge of VAC spatial patterns and prevalence at the population level.

5. Conclusions

In conclusion, our review provides essential insights for applying geospatial analysis to understand the spatial patterns and disparities of VAC globally. The findings indicated an increasing trend in published articles on VAC geospatial analysis since 2015, focusing mainly on child maltreatment. However, there is a notable imbalance in the geographical distribution of studies, with the majority conducted in HICs and limited investigations in LMICs. Additionally, we identified challenges related to the use of administrative data that may frequently produce incomplete and unreliable estimates owing to collection errors. It will be beneficial if future studies provide a detailed account of the study design, leverage small-scale geospatial data collected directly from children, and report the desired key methodological aspects within the geospatial modelling framework outlined in this review to improve research quality and transparency. Applying geospatial analysis offers valuable insights for identifying areas of high- and low-risk of the prevalence of VAC, enabling the redistribution of resources and intervention strategies to highly affected areas. Distributing resources where they are most needed can help meet the global goal of ending the VAC.

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Tobias Willem Shinyemba: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shino Shiode:** Writing – review & editing, Validation, Supervision, Methodology, Data curation, Conceptualization. **Karen Devries:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chiabu.2024.106730.

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