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The impact of neighbourhood crime on mental health: A systematic review and meta-analysis

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ABSTRACT

Background: Growing evidence indicates that the residential neighbourhood contributes to the complex aetiology of mental disorders. Although local crime and violence, key neighbourhood stressors, may be linked to mental health through direct and indirect pathways, studies are inconclusive. This systematic review and meta-analysis aimed to synthetize the evidence on the association between neighbourhood crime and individual-level mental health problems.

Method: We searched 11 electronic databases, grey literature and reference lists to identify relevant studies published before September 14, 2020. Studies were included if they reported confounder-adjusted associations between objective or perceived area-level crime and anxiety, depression, psychosis or psychological distress/internalising symptoms in non-clinical samples. Effect measures were first converted into Fisher's z-s, pooled with three-level random-effects meta-analyses, and then transformed into Pearson's correlation coefficients. Univariate and multivariate mixed-effects models were used to explore between-study heterogeneity.

Results: We identified 63 studies reporting associations between neighbourhood crime and residents' mental health. Pooled associations were significant for depression ($r = 0.04$, 95% CI 0.03–0.06), psychological distress ($r = 0.04$, 95% CI 0.02–0.06), anxiety ($r = 0.05$, 95% CI 0.01–0.10), and psychosis ($r = 0.04$, 95% CI 0.01–0.07). Moderator analysis for depression and psychological distress identified stronger associations with perceived crime measurement and weaker in studies adjusted for area-level deprivation. Importantly, even after accounting for study characteristics, neighbourhood crime remained significantly linked to depression and psychological distress. Findings on anxiety and psychosis were limited due to low number of included studies.

Conclusions: Neighbourhood crime is an important contextual predictor of mental health with implications for prevention and policy. Area-based crime interventions targeting the determinants of crime, prevention and service allocation to high crime neighbourhoods may have public mental health benefits. Future research should investigate the causal pathways between crime exposure and mental health, identify vulnerably groups and explore policy opportunities for buffering against the detrimental effect of neighbourhood stressors.

1. Introduction

Mental health problems are major contributors to disability and suffering (Vos et al., 2017), affecting 30% of the global population at least once during their lifetime (Steel et al., 2014). Over and above individual and household-level factors, there is a growing understanding that social and physical features of the living environment may contribute to the complex multifactorial aetiology of mental disorders (Diez Roux, 2007; Lund et al., 2018; O'Brien et al., 2019; Richardson et al., 2015). Crime and violence in the community is a major public concern, included in the Sustainable Development Goals (Lund et al., 2018), and identified as key stressor likely mediating the impact of neighbourhood characteristics on mental ill health (Lorenc et al., 2012; Galster, 2012). Research in criminology indicates that the spatial distribution of crime events is not random. Increased crime rates are more common in disadvantaged and low-income neighbourhoods (Sampson

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et al., 1997), and in areas with signs of social disorganisation and low collective efficacy (i.e. social cohesion among neighbours with effective control to regulate members maintaining desired common goals) (Sampson et al., 1997). Within neighbourhoods, crime incidents are particularly concentrated around micro-geographic units, such as street segments, where criminogenic characteristics (e.g. lack of local guardianship, suitable targets) provide opportunities for offending (Jones and Pridemore, 2018).

Neighbourhood crime can impact mental health through direct and indirect pathways (Lorenc et al., 2012). Becoming a victim or witnessing crime in the community increases the risk of developing mental disorders, in particular for post-traumatic stress disorder and depression (Fowler et al., 2009; Lorenc et al., 2012; Lund et al., 2018; Sharkey, 2018; Tan and Haining, 2016). There is, however, less evidence and consensus on whether living in residential communities with higher crime and violence impacts mental health, and what the pathway are, regardless of direct individual exposure. It is plausible that neighbourhood crime is an ecological stressor leading to activated stress response in unsafe areas or to behavioural avoidance affecting engagement in physical and social activities (Lorenc et al., 2012). As likely more people (i.e. entire communities) are affected by the indirect impact of crime, understanding whether and how neighbourhood-level crime is linked to mental health and 'gets under the skin' is crucial for public health. Neighbourhood crime can be operationalised as the subjective perception of study participants indicating danger or safety in their area, or studies may rely on objective measures capturing administrative records on crime incidents, independent of participants' perception. While perceived crime likely mediates the impact of objective crime on mental health, evidence is lacking on studies including both measures (Wilson-Genderson and Pruchno, 2013).

Despite the considerable public health and policy relevance (Lorenc et al., 2012; Lund et al., 2018), there is no systematic review and meta-analysis available on the impact of neighbourhood crime on mental health. We aimed to fill this gap by reviewing the literature on the quantitative association between perceived and objective area-level crime and individual-level mental health in non-clinical populations. Establishing the relationship for anxiety, depression, psychosis and psychological distress/internalising symptoms across the life course, and exploring the heterogeneity between studies can provide further insights into the complex crime-mental health relationship.

2. Method

This systematic review and meta-analysis followed the Meta-analysis Of Observational Studies in Epidemiology (MOOSE) guidelines (Stroup et al., 2000); the research protocol was published on PROSPERO (CRD42019141371).

2.1. Search strategy and selection criteria

We developed a multi-stage search strategy to identify relevant literature on the association between neighbourhood crime and mental health (Supplementary Appendix 1). Searches were updated on the September 14, 2020 and comprised: 11 online databases (ASSIA, CAB Abstracts, Embase, Global Health, IBSS, MEDLINE, PsycINFO, Scopus, Social Services Abstracts, Sociological Abstracts and Web of Science), grey literature (OpenGrey) and screening reference lists of included papers and relevant reviews (Lorenc et al., 2012; O'Brien et al., 2019). We corresponded with authors to clarify methodology or results. Publications from all languages were considered. Database-specific search terms combining free-text strings and subject headings with Boolean operators (AND, OR, ADJn) can be found in Supplementary Table 1.

Quantitative studies meeting the following criteria were included: (1) the sample was recruited with representative sampling techniques from non-clinical populations (e.g. children in schools, employees, older adults in retirement); (2) local crime was captured as objectively recorded or perceived; (3) mental health outcomes (anxiety, depression, psychosis, psychological distress/internalising symptoms) were assessed with symptom scales, diagnostic instruments or service use data; and (4) confounder-adjusted main effects were reported. Adjustments for at least sex, age and individual-level socioeconomic status, key predictors of neighbourhood crime exposure and mental health, were required. If studies failed to control for socioeconomic status, we accepted adjustment for ethnicity as a proxy of socioeconomic disadvantage.

We excluded studies when: (1) the sample was based on individuals or their offspring with chronic physical or mental health conditions, as associations might differ in clinical samples (Generaal et al., 2019), or recruitment was convenient; (2) the predictor was (i) direct exposure to community crime (i.e. victimisation, witnessing crime), where reviews are already available (Fowler et al., 2009), (ii) fear of crime, because of a high risk of reverse causation with mental disorders (Foster et al., 2016; Lorenc et al., 2012), or (iii) perceived crime was measured by a composite questionnaire with $\leq$50% crime-related items to avoid the inclusion of related concepts (e.g. neighbourhood disorder, general safety); (3) the outcome was operationalised as mental well-being, perceived stress or a non-specified mental illness; (4) univariate associations were reported or studies utilised aggregated mental health data prone to ecological fallacy. (5) Finally, duplicate studies without sufficient differences in the design or variable operationalisation, as well as (6) conference abstracts and papers without original data were excluded. Two reviewers (GB, MHDM) screened all publications independently. Where there was disagreement a third reviewer (JP) was included in the appraisal.

2.2. Data extraction and quality appraisal

GB extracted and MHDM cross-checked the following information from the included studies: authors, year of publication, geographic location, data source, target population, sample size, sample characteristics (age, sex), sampling technique, baseline response rate, study design (cross-sectional, longitudinal, case-control), follow-up time and loss to follow-up for longitudinal studies, crime measurement, area of crime exposure, covariates, outcome assessment and risk estimates.

We classified objective and perceived (individual-level or aggregated) crime measures into violent (e.g. murder, manslaughter, robbery and assault), property (e.g. burglary, larceny, theft, arson, and vandalism) and mixed crimes; if studies reported effect sizes for multiple single crime types, we pooled them into one of the main groups using fixed-effects meta-regression (Meffert et al., 2015). Mental health problems were classified into four groups, capturing symptoms, diagnosis or service use related to psychotic, depressive, and anxiety disorders; for psychosis we included related concepts such as psychotic experiences and ultra-high risk state of psychosis. The fourth group was designated to combined symptoms of depressive and anxiety disorders, also known as psychological distress, or internalising symptoms among people under 18. We considered samples as the main units of analyses, rather than individual studies: for each exposure and outcome combination we extracted a maximum of one cross-sectional and one longitudinal (with the longest follow-up) effect estimate per sample.

To account for the area of crime exposure, we estimated the average population size in administrative units or participant-centred buffer zones. Mental health assessments were coded whether they applied broader (e.g. symptom scales, medications) or narrower (e.g. diagnosis based on clinical interview, patient registries) criteria. In addition to the continuous age indicator, we classified age groups to account for nonlinear associations: childhood (7–12 years), adolescence (13–18), or adulthood (19+); the latter was subdivided into young adulthood (19–35), middle adulthood (36–60) and late adulthood (61<). Furthermore, we coded whether extracted estimates were adjusted for individual-level crime exposure, presenting the direct crime-mental health pathway; and for area-level socioeconomic status or neighbourhood social processes (e.g. social disorganisation, social cohesion), main predictors of crime incidents. In order to extract comparable effect estimates across all included studies: (i) we selected the most comprehensive model adjusted for all individual characteristics, but without including interactions or controlling for other neighbourhood covariates; (ii) we chose the smallest level of aggregation if relevant data was available (Chaix et al., 2006; Dustmann and Fasani, 2016; Villarreal and Yu, 2017; Weisburd et al., 2018); and (iii) when exposure was presented in non-overlapping groups (e.g. tertiles), we extracted the strongest indicative estimate, as neighbourhood crime-mental health relationship might not be linear (Ramey and Harrington, 2019).

Two reviewers (GB, MHDM) appraised quality of included studies using the National Institutes of Health's Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies (NIH National Heart Lung and Blood Institute, n.d.). We applied a modified version of the scale comprising 13 questions on study design, exposure and outcome measurement, and statistical approach. Summary scores ranging between 0 and 13 were calculated for each extracted estimates and were considered as 'poor' from 0 to 4, 'fair' from 5 to 9 and 'good' from 10 to 13 points (Supplementary Appendix 2).

2.3. Statistical procedure

Prior to analyses, effect measures were converted into a common metric using the *esc* package in R (Lüdecke, 2019). For binary outcomes, Fisher's z-s were directly calculated based on estimates, standard errors and sample sizes; for continuous outcomes, we first computed t-values and then Fisher's z-s (Jacobson and Newman, 2017). Missing information was calculated using standard formulas (Higgins and Green, 2011), and if no indication of precision was reported, we imputed $p = 0.5$ for non-significant and $p = 0.05$ for significant associations. Although we used Fisher's z-s in the analysis to prevent biases arising from the skewed distribution of Pearson's correlation coefficients (r); findings are reported in r-s after backtransformation (Jacobson and Newman, 2017).

To account for dependency between estimates derived from the same sample, we fitted three-level meta-analyses — which decompose the total variance into sampling (level 1), between-estimates (level 2) and between-sample variance (level 3) (Moeyaert et al., 2016) — and added random-effects at the estimate and sample levels. Models were fitted with the restricted maximum-likelihood estimation, and pooled effect sizes were calculated with Knapp-Hartung adjustments for confidence intervals using the *metafor* package in R (Viechtbauer, 2010), Significant Cochrane's Q-statistics indicated heterogeneity between estimates. Intercept (r) only models were run separately for anxiety, depression, psychosis and psychological distress to express their global association with area-level crime.

To explore heterogeneity, we conducted univariate mixed-effects models (i.e. meta-regression) with key moderators included as fixed effects (Viechtbauer, 2010) when at least 10 estimates within the same outcome group were available (Higgins and Green, 2011). First, predicted estimates across different study designs and crime measurements were calculated by fitting the models without intercept. Second, models with intercept estimated differences between the levels of the following moderators: % female; age (continuous); age groups (categorical); population (non-disadvantaged vs disadvantaged); area of crime exposure; crime measurement; types of crime; study design; adjustment for individual crime exposure, neighbourhood deprivation, social processes; and quality score. If at least 20 estimates were available, significant moderators ($p \leq 0.05$) were retained for multivariate models. Intercepts (r) in these multivariate models indicated average area-level crime associations after taking into account the effects of potential moderators (latter were expressed in unstandardized regression coefficients [B]).

Inter-rater agreement between reviewers were calculated with Cohen's Kappa (Higgins and Green, 2011). Publication bias was assessed with funnel plots of estimates against their standard errors with the rank correlation test assessing funnel plot asymmetry (Viechtbauer, 2010). We conducted four sensitivity analyses: (1) After identifying potential outliers and influential cases (Viechtbauer and Cheung, 2010), main meta-analyses were rerun without these estimates. (2) To further account for the dependency between effect sizes derived from the same samples, robust variance estimations were calculated (Moeyaert et al., 2016). (3) We conducted meta-analysis separately for studies utilising survey data and information on accessed mental health service use. (4) Finally, as transforming continuous outcomes using t-values likely introduces bias into the transformed effect size, we recalculated pooled estimates for binary and continuous outcomes separately (Jacobson and Newman, 2017). For binary outcomes, ORs were transformed into RRs (Grant, 2014) and pooled directly (forest plots are shown in the main text); for continuous outcomes we retained Fisher's z (forest plots are shown in supplementary material).

3. Results

Out of 10,854 unique records, we included 63 studies in the meta-analyses with good agreement rates between reviewers (Cohen's Kappa = 0.73) (Fig. 1). Studies were published between 2002 and 2021 in a wide range of disciplines (e.g. psychology, public health, economics, criminology) and based on over 700,000 individual mental health assessments. Objectively measured crime was used in 37 studies, while 25 assessed perceived crime; one study included both. Table 1 describes the studies included with details on study design, sample characteristics, exposure and outcome measurement, and quality assessment; Table 1A for studies with objectively measure crime and Table 1B for studies with perceived neighbourhood crime. Studies are sorted by outcome groups. Across the four outcomes 103 study estimates were extracted, for which descriptive statistics can be found in Table 2.

3.1. Main analyses

Depression. Meta-analyses indicated an increased risk of depression in higher crime areas (r = 0.04, 95% CI 0.03–0.06), with substantial heterogeneity (Cochran's Q = 225.17) between the 50 estimates (Table 3); the link was present across all different study designs and types of crime measurement (Table 4). Associations were stronger among young adults (B = 0.123, 95% CI 0.057–0.188), in studies utilising individual-level perceived crime (B = 0.051, 95% CI 0.026–0.077), and weaker when area-level deprivation was adjusted for (B = −0.039, 95% CI -0.067–0.011) (Table 5). After retaining statistically significant predictors in the multivariate mixed-effects models, studies based on young adults (B = 0.088, 95% CI 0.028–0.148) and individual-level perceived crime (B = 0.034, 95% CI 0.006–0.062) had stronger crime-depression associations. More importantly, in this multivariate model, the intercept remained significant indicating a robust association between neighbourhood crime and depression (r = 0.03, 95% CI 0.01–0.05) (Table 5).

Psychological distress/internalising symptoms. The pooled association between crime and psychological distress/internalising symptoms was significant (r = 0.04, 95% CI 0.02–0.06) (Table 3) but with high heterogeneity between the 37 estimates (Cochran's Q = 155.03). Estimates were significant across all study designs and types of crime measurements (Table 4). Studies of older adults had stronger associations (B = 0.118, 95% CI 0.036–0.201), while those adjusted for area deprivation (B = −0.035, 95% CI -0.067–0.004) had weaker associations; on threshold level (p = 0.05), studies with individual-level perceived crime measurement had stronger associations (B = 0.037, 95% CI -0.000-0.075) (Table 5). Multivariate models showed stronger crime-psychological distress associations among older adults (B = 0.124, 95% CI 0.044–0.204) and when individual-level perceived crime was measured (B = 0.039, 95% CI 0.005–0.073). Finally, the neighbourhood crime intercept remained significantly associated with psychological distress in the multivariate model (r = 0.03, 95% CI 0.00–0.06) (Table 5).

Anxiety and psychosis. The meta-analysed results indicated

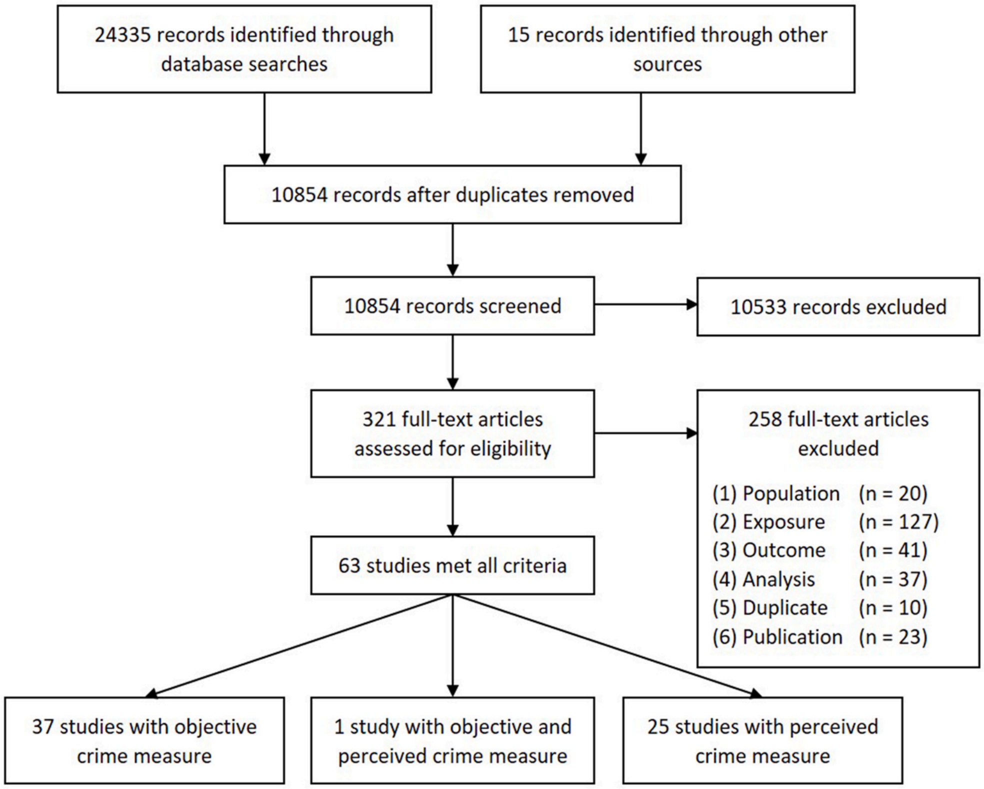

Fig. 1. Study identification, screening and eligibility test, following the Preferred Reporting Items of Systematic Reviews (PRISMA).

significant pooled neighbourhood crime-anxiety (r = 0.05, 95% CI 0.01–0.10; Cochran's Q = 19.00) and neighbourhood crime-psychosis associations (r = 0.04, 95% CI 0.01–0.06; Cochran's Q = 18.45) (Table 3). The small number of included estimates precluded further analyses of anxiety (k = 8) and psychosis (k = 8).

3.2. *Study quality*

Overall, 50 studies were graded as having 'fair' quality, 12 studies were graded as 'good' and only 1 study had 'poor' quality; no study reached the highest possible quality rating using our modified scale (Supplementary Table 2). A particular problem was the lack of information on methodological aspects of studies (e.g. baseline response rate, follow up rate), which affected the overall quality score of included investigations. In univariate meta-regression, we explored whether quality score (ranging from 0 to 13) explained the heterogeneity between estimates. Our results indicated that study quality did not significantly influence crime estimates for depression (B = −0.003, 95% CI -0.010-0.004) and psychological distress (B = −0.000, 95% CI -0.011-0.011) (Table 5).

3.3. *Sensitivity analysis*

Publication bias could only be detected among studies with depression as outcome (Kendall's tau = 0.20; $p < 0.05$; Supplementary Figure 1). Outlier and influence diagnostic identified two outlier estimates for depression (Mair et al., 2010; Secretti et al., 2019) and one for psychological distress (Astell-Burt et al., 2015) (Supplementary Figure 2); after excluding them from the analyses the pooled associations decreased but remained significant for depression (r = 0.03, 95% CI 0.02–0.05) and psychological distress (r = 0.03, 95% CI 0.02–0.05). Moreover, after exclusion of outliers publication bias was no longer present for depression (Kendall's tau = 0.17; p = 0.10; Supplementary Table 3). The main results did not materially change when robust variance estimations were calculated (Supplementary Table 4) or when estimates derived from mental health service use data were excluded (Supplementary Table 5).

Finally, we pooled binary and continuous outcome measures separately across the 4 outcomes. Results based on binary outcomes indicated 8% (RR = 1.08, 95% CI 1.03–1.14) higher risk of depression and 25% higher risk of psychological distress (RR = 1.25, 95% CI 1.08–1.44) if living in high compared to low crime neighbourhoods. Associations were close to significance thresholds for psychosis (RR = 1.16, 95% CI 1.00–1.35) and anxiety (RR = 1.25, 95% CI 0.97–1.62) (Fig. 2). For continuous outcomes, the association with depression (r = 0.05, 95% CI 0.03–0.07) and psychological distress (r = 0.03, 95% CI 0.01–0.04) also remained significant (Supplementary Figure 3).

4. Discussion

This systematic review and meta-analysis suggests that residing in high crime areas is linked to mental health problems. Associations were more robust for depression and psychological distress, where further analyses uncovered stronger links in studies utilising individual-level perceived crime assessment, were weaker when adjusting for area-level deprivation and showed varying vulnerability across the life-course. While we were able to identify an indication of higher risk of anxiety and psychosis in high crime neighbourhoods, these were based on a small number of studies.

To our knowledge, this is the first comprehensive systematic review and meta-analysis of the association between neighbourhood crime and mental health, and, more broadly, one of the first to consider the neighbourhood determinants of mental health (O'Brien et al., 2019; Richardson et al., 2015). More robust results based on the binary outcomes indicated an 8–25% increased risk of mental ill health in high crime areas. Although these are relatively small, effect sizes of this magnitude are common in the literature on area effects (O'Brien et al., 2019; Richardson et al., 2015) and comparable to well-established

Table 1
Studies reporting the association between (A) objectively measured and (B) perceived neighbourhood crime and mental health.

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime		Outcome measure	Control for		QA[a]
						Type	Area unit		Area SES	Direct crime exposure	
I. Anxiety											
Baranyi et al. (2020a)	Scotland, UK	Scottish Longitudinal Study	Adulthood	129,945	L	MC	Data zone	Service use (anxiolytic medication)	–	No	10
Chaix et al. (2006)	Malmö, Sweden	–	Middle adulthood	89,285	C	VC	500 m radius	Service use (diagnosis [ICD-10: F40–F48])	–	No	9.5
Cuartas & Roy (2019)	Bogotá, Colombia	Colombian Mental Health Survey	Adolescence	300	C	VC	150 m buffer around the residential block	PCL	–	Yes	8
Mattocks (2019)	Baltimore, US	Healthy Aging in Neighborhoods of Diversity across the Life Span	Adulthood	2006	C	PC	Census tract	PDSQ-GAD	Poverty	No	9
Weisburd et al. (2018)	Baltimore, US	–	Adulthood	2136	C	VC	Street segments	Short Screening Scale for DSM-IV PTSD	–	No	8.5
II. Depression											
Baranyi et al. (2020a)	Scotland, UK	Scottish Longitudinal Study	Adulthood	129,945	L	MC	Data zone	Service use (antidepressant medication)	–	No	10
Beck et al. (2017)	Denver, US	Kaiser Permanente, Denver Health	Adulthood	165,600	C	MC	Census tract	Service use (diagnosis [ICD-9: 296.x, 298.0, 300.4, 309.x, 311])	Education, Poverty, Income, Housing tenure, Public assistance, Employment	No	9.5
Chen & Chen (2015)	Urban China	Migration and Quality of Life Survey	Adulthood	1250	C	MC	Urban prefecture	CESD-8	GDP	No	8
Dustmann & Fasani (2016)	England, UK	English Longitudinal Study of Ageing	Late adulthood	~16,600 observations	L	MC	Local Authority	Modified CESD	Welfare benefiters	No	9.5
Generaal et al. (2019)	The Netherlands	Netherlands Mental Health Survey and Incidence Study-2; Healthy Life in an Urban Setting study; Netherlands Twin Register; New Hoorn Study; Longitudinal Aging Study Amsterdam; Generations[2]	Adulthood	28,444	C	MC	Four-digit postal code	CIDI; PHQ-9; HADS-D; CESD-20; BDI-II	–	No	7
Gepty et al. (2019)	Philadelphia, US	Adolescent Cognition and Emotion	Adolescents	309	L	VC, PC	Police district	CDI	–	No	8
Hessel et al. (2019)	4 cities in Colombia	2010 Demographic and Health Survey	Late adulthood	2227	C	VC	250 m radius	Modified Zung self-rating depression scale	–	No	10
Joshi et al. (2017)	New York City, US	New York City Neighbourhood and Mental Health in the Elderly Study II	Late adulthood	2023	L	VC	1-km buffer	PHQ-9	Poverty	No	10
Mattocks (2019)	Baltimore, US	Healthy Aging in Neighborhoods of Diversity across the Life Span	Adulthood	2006	C	PC	Census tract	CESD-20	Poverty	No	9
Meng et al. (2017)	Montreal, Canada	Montreal South-West Longitudinal Catchment Area study	Adulthood	1357	L	MC	500-m buffer	CIDI	Income, Employment	No	6.5
Norstrand, 2015	Philadelphia, US	Community Health Data Base	Adulthood	983	C	VC	Census tract	CESD-10	Income	No	8
Tracy (2012)	Detroit, US	Detroit Neighbourhood Health Study	Adulthood	1037	L	VC	City neighbourhood	PHQ-9	–	Yes	9
Weisburd et al. (2018)	Baltimore, US	–	Adulthood	2136	C	VC	Street segments	PHQ-9	–	No	8.5
Wilson-Genderson & Pruchno (2013)	New Jersey, US	Ongoing Research on Aging in New Jersey: Bettering Opportunities for Wellness in Life	Late adulthood	5688	C	VC	Census tract	CESD-10	–	No	9
III. Psychosis											

(*continued on next page*)

Table 1 (*continued*)

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime		Outcome measure	Control for		QA[a]
						Type	Area unit		Area SES	Direct crime exposure	
Baranyi et al. (2020a)	Scotland, UK	Scottish Longitudinal Study	Adulthood	129,945	L	MC	Data zone	Service use (antipsychotic medication)	–	No	10
Bhavsar et al. (2014)	London, UK	Lambeth Early Onset	Young adulthood	Person at risk: 267,000; Incidence: 405	CC	MC	Lower Super Output Are	Service use (first episode of schizophrenia)	Income, Employment; Education	No	9
Bhavsar et al. (2018)	London, UK	Outreach and Support in South London	Young adulthood	Person-years at risk: 2,347,022; Incidence: 336	CC	MC	Lower Super Output Area	Service use (ultra-high-risk for psychosis [CAARMS])	–	No	9
Karcher et al. (2021)	21 sites across the US	Adolescent Brain Cognitive Development study	Childhood	10,328	C	MC	County	Psychotic experiences (PQ-BC)	Deprivation	No	6.5
Newbury et al. (2017)	England and Wales, UK	Environmental Risk Longitudinal Twin Study	Adolescence	2232	L	MC	1-mile buffer	Psychotic experiences	Poverty	No	11
Veling et al. (2015)	Hague, The Netherlands	–	Adulthood	Person at risk: 277,008; Incidence: 618	CC	MC	Postal code area	Service use (first episode of psychosis [CASH])	–	No	7
IV. Psychological distress/Internalising symptoms											
Alcock et al. (2015)	Rural England, UK	British Household Survey Panel	Adulthood	2200	L	MC	Lower Super Output Area	GHQ-12	Income, Employment, Education	No	9
Ambrey & Shahni (2017)	Teheran, Iran	Urban Health Equity Assessment and Response Tool-2	Adulthood	19,060	C	PC	City districts	GHQ-28	–	No	6
Astell-Burt et al. (2015)	New South Wales, Australia	45 and Up Study	Late adulthood	54,844	L	MC	Statistical Local Area	K10	–	No	10
Baranyi et al. (2020a)	Scotland, UK	Scottish Longitudinal Study	Adulthood	129,945	L	MC	Data zone	Service use (anxiolytic or antidepressant medication)	Income	No	10
Brooks Holliday et al. (2019)	Pittsburgh, US	Pittsburgh Hill/Homewood Research on Neighborhoods, Sleep, and Health Study	Middle adulthood	820	C	MC	1 km radius	K6	–	No	6
Cornaglia et al. (2014)	Urban Australia	Household, Income, and Labor Dynamics in Australia	Adulthood	32,594 observations	L	VC, PC	Local Governmental Area	MCS	Employment, Income	Yes	9
Cuartas & Leventhal (2020)	Bogotá, Colombia	Colombian Mental Health Survey	Childhood	404	C	VC	Residential block	Modified RQC	–	Yes	8
Cuartas & Roy (2019)	Bogotá, Colombia	Colombian Mental Health Survey	Adolescence	300	C	VC	150 m buffer around the residential block	Modified RQC	–	Yes	8
Dustmann & Fasani (2016)	England and Wales, UK	British Household Panel Survey	Adulthood	~35,000 observations	L	MC	Local Authority	GHQ-12	Welfare benefiters	No	10
Fagg et al. (2006)	London, UK	Research with East London Adolescents: Community Health Survey	Adolescence	2370	C	MC	Middle Layer Super Output Areas	SDQ	–	No	8
Flouri et al. (2020)	UK	Millennium Cohort Study	Childhood	5918	L	MC	Lower Super Output Area	SDQ	–	No	9
Goldman-Mellor et al. (2016)	California, US	California Health Interview Survey	Adolescence	4462	C	VC	Census tract	K6	Socioeconomic disadvantage	No	7
Karcher et al. (2021)	21 sites across the US	Adolescent Brain Cognitive Development study	Childhood	10,328	C	MC	County	CBCL	Deprivation	No	6.5
Long (2005)	Baltimore, US	–	Adulthood	270	L	MC	Census block neighbourhoods	Combined STAI and CESD-6	Housing tenure, SES	Yes	12
McCoy et al. (2016)	Chicago, US		Childhood	327	C	MC	Census tract	TRF	Education, Poverty	Yes	7

(*continued on next page*)

Table 1 (*continued*)

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime: Type	Neighbourhood crime: Area unit	Outcome measure	Control for: Area SES	Control for: Direct crime exposure	QA[a]
		Chicago School Readiness Project; Chicago Head Start									
Pearson & Breetzke (2013)	New Zealand	New Zealand General Social Survey	Adulthood	~8550	C	MC	Census area unit	MCS-12	Deprivation	Yes	8.5
Polling et al. (2014)	London, UK	South East London Community Health	Adulthood	1698	C	MC	Lower Super Output Area	CIS-R	–	Yes	9
Ramey & Harrington (2019)	11 cities in the US	Fragile Families and Child Wellbeing Study	Childhood	1212	L	VC, PC	Census tract	Internalising behaviour scores	Concentrated disadvantage	No	8
Stockdale et al. (2007)	US	Health Care for Communities	Adulthood	12,716	C	VC	County	CIDI-SF	Income, Home ownership	Yes	7
Villarreal & Yu (2017)	Mexico	Mexican Family Life Survey	Adulthood	30,749	L	VC	Municipalities	Modified GHQ	–	Yes	11
White et al. (2013)	Urban England, UK	British Household Panel Survey	Adulthood	12,818	L	MC	Lower Super Output Area	GHQ-12	Income, Employment, Education	No	9.5

(B)

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime: Type	Neighbourhood crime: Assessment (Individual or Aggregated)[b]	Outcome measure	Control for: Area SES	Control for: Direct crime exposure	QA[a]
I. Anxiety											
Secretti et al. (2019)	6 state capitals in Brazil	Brazilian Longitudinal Study of Adult Health	Adulthood	10,392	C	MC	Individual: (1) feeling safe walking day or night; (2) violence is a problem; (3) neighbourhood is safe with regard to crimes	CIS-R	–	No	7
Schriber et al. (2017)	Northern California, US	California Families Project	Adolescence	209	L	MC	Individual: (1) violent crimes (e.g. stabbings, shootings, assaults); (2) taking others' wallets or purses; (3) damaging property; (4) breaking into homes and cars; (5) throwing trash in the streets/breaking glass; (6) gang fights; (7) drug use and dealing; (8) alcohol use in public; (9) graffiti; (10) groups of people making feel unsafe; (around schools and homes)	SCARED	–	No	7
Simning et al. (2012)	US	National Survey of American Life	Adulthood	2820	C	MC	Individual: (1) problems with muggings, burglaries, assaults or anything else like that	CIDI	–	No	7
II. Depression											
Baranyi et al. (2019)	13 European countries	The Survey of Health, Ageing and Retirement in Europe	Late Adulthood	10,328	L	MC	Individual: (1) vandalism, crime	EURO-D	–	No	9
Forehand & Jones (2003)	New Orleans, US	The Family Health Project	Childhood	117	C/L	VC	Individual: (1) physical fighting, (2) shootings or knifings, (3) people being killed	CDI	–	No	6
Jones et al. (2005)	New Orleans, US	The Family Health Project	Childhood	137	C	MC	Individual: (1) gangs; (2) physical fighting; (3) shootings or knifings; (4) people being killed; (5) drug use or drug dealing	CDI	–	No	4.5
Kim (2012)	Metropolitan areas of Miami/Ft. Lauderdale, San Diego, US	Children of Immigrants Longitudinal Study	Adolescence	2114	C	MC	Individual: (1) racial or cultural groups do not get along; (2) little respect for rules, laws and authority; (3) assaults and muggings; (4) delinquent gangs or drug gangs; (5) drug use or drug dealing in the open	CESD-4	–	No	5
Lin et al. (2019)	Taiwan	–	Late Adulthood	1025	C	MC	Individual: (1) safety from crimes at night	GDS-4	–	No	6

(*continued on next page*)

Table 1 (*continued*)

(B)

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime: Type	Neighbourhood crime: Assessment (Individual or Aggregated)[b]	Outcome measure	Control for: Area SES	Control for: Direct crime exposure	QA[a]
Lowe et al. (2014)	Jamaica, St. Vincent, St. Kitts and Nevis, The Bahamas	–	Adolescence	1955	C	MC	Individual: (1) fight with a weapon; (2) youth gang conflict; (3) people hit by police; (4) someone badly hurt; (5) burglary of homes; (6) mugging or robbery; (7) assault by strangers; (8) people afraid to go out after dark; (9) you take a big risk walking alone after dark	BDI-II	–	No	6.5
Mair et al. (2015)	New York City, US	Multi-Ethnic Study of Atherosclerosis	Late Adulthood	548	L	VC	Aggregated (census tract): (1) fight in which a weapon was used; (2) gang fight; (3) sexual assault or rape; (4) robbery or mugging	CESD-20	–	No	10.5
						MC	Aggregated (census tract): (1) safe walking day or night; (2) violence is not a problem; (3) neighbourhood is safe from crime				
Mair et al. (2010)	Chicago, US	Chicago Community Adult Health Study	Adulthood	3105	C	VC	Individual/Aggregated (cluster): (1) fight in which a weapon was used; (2) gang fight; (3) sexual assault or rape; (4) robbery or mugging	CESD-11	–	No	8.5
Meffert et al. (2015)	South Africa	South African National Income Dynamics Study	Adulthood	7173	C/L	VC	Individual: (1) burglary/mugging/theft; (2) violence between members of the same household; (3) violence between members of different households; (4) gangsterism; (5) murder/shootings/stabbings	CESD-10	–	No	10
Moore et al. (2016)	6 cities in the US	Multi-Ethnic Study of Atherosclerosis	Late Adulthood	5475	L	MC	Individual/Aggregated (1-mile buffer): (1) feel safe walking day or night; (2) violence is not a problem; (3) neighbourhood is safe from crime	CESD-20	–	No	11
Schriber et al. (2017)	California, US	California Families Project	Adolescence	209	L	MC	Individual: (1) violent crimes (e.g. stabbings, shootings, assaults); (2) taking others' wallets or purses; (3) damaging property; (4) breaking into homes and cars; (5) throwing trash in the streets/breaking glass; (6) gang fights; (7) drug use and dealing; (8) alcohol use in public; (9) graffiti; (10) groups of people making feel unsafe; (around schools and homes)	CDI-2	–	No	7
Secretti et al. (2019)	6 state capitals in Brazil	Brazilian Longitudinal Study of Adult Health	Adulthood	10,392	C	MC	Individual: (1) feeling safe walking day or night; (2) violence is a problem; (3) neighbourhood is safe with regard to crimes	CIS-R	–	No	7
Simning et al. (2012)	US	National Survey of American Life	Adulthood	2820	C	MC	Individual: (1) problems with muggings, burglaries, assaults or anything else like that	CIDI	–	No	7
Simons et al. (2002)	Iowa and Georgia, US	Family and Community Health Study	Childhood	810	C	VC	Aggregated (clusters): (1) violent arguments; (2) fights with weapons; (3) robbery; (4) gang conflict, (5) sexual assault	DISC-IV	Poverty	Yes	6
Tamura et al. (2020)	Jackson, US	Jackson Heart Study	Adulthood	2209	C	VC	Aggregated (census tract): (1) violent arguments; (2) fights with weapons; (3) robbery; (4) gang conflict, (5) sexual assault	CESD-20	–	No	7
Teychenne et al. (2012)	Victoria, Australia	Resilience for Eating and Activity Despite Inequality Study	Young adulthood	4065	C	MC	Individual: (1) feeling safe walking day or night; (2) neighbourhood is safe from crime; (3) violence is not a problem	CESD-10	–	No	5
Tomita et al. (2015)	South Africa	South African National Income Dynamics Study	Adulthood	13,593	C	MC	Aggregated (clusters): (1) burglaries, muggings or thefts; (2) violence between members of the same household; (3) violence between members of different households; (4)	CESD-10	–	No	7

(*continued on next page*)

Table 1 (*continued*)

(B)

Reference	Location	Data sources	Age group	Sample size	Study design	Neighbourhood crime		Outcome measure	Control for		QA[a]
						Type	Assessment (Individual or Aggregated)[b]		Area SES	Direct crime exposure	
							gangsterism; (5) murder, shootings or stabbings; (6) drug or alcohol abuse				
III. Psychosis											
Kirkbride et al. (2008)	South London, UK	Aetiology and Ethnicity in Schizophrenia and Other Psychoses	Adulthood	Person-years at risk: 565,576; Incidence: 148	CC	MC	Aggregated (ward): (1) graffiti; (2) teenagers hanging around; (3) drunks or tramps on the streets; (4) vandalism and deliberate damage to property; (5) insults or attacks to do with someone's race or colour; (6) homes broken in to; (7) cars broken in to or stolen; (8) people attacked on the streets	Service use (first episode of schizophrenia [SCAN])	Deprivation	No	9
Karcher et al. (2021)	21 sites across the US	Adolescent Brain Cognitive Development study	Childhood	10,328	C	MC	Individual: (1) feeling safe walking day or night; (2) violence is not a problem; (3) neighbourhood is safe with regard to crimes	Psychotic experiences (PQ-BC)	Deprivation	No	6.5
IV. Psychological distress/Internalising symptoms											
Benjet et al. (2019)	5 Latin American cities	World Mental Health Surveys	Adulthood	7251	C	VC	Aggregated (various): (1) experienced any violent event	CIDI	Education	Yes	10
Bostean et al. (2018)	US	National Latino and Asian American Survey; Latino sample	Adulthood	2524	C	MC	Individual: (1) feeling safe alone in the at night; (2) people get mugged; (3) people sell/use drugs	K10	–	No	6
Delgado et al. (2012)	Western Andalusia, Spain	–	Adolescence	2400	C	MC	Individual: (1) people sell drugs; (2) some of my friends are afraid to come to my neighbourhood; (3) crimes and hooliganism; (4) fights between street gangs	YSR	–	No	5.5
Fauth et al. (2007)	Chicago, US	Project on Human Development in Chicago Neighborhoods; 9-, and 12-year-olds	Childhood	1315	L	VC	Aggregated (clusters): (1) fight in which a weapon was used; (2) violent argument between neighbours; (3) gang fight; (4) sexual assault or rape; (5) robbery or mugging	CBCL	–	No	12
Karcher et al. (2021)	21 sites across the US	Adolescent Brain Cognitive Development study	Childhood	10,328	C	MC	Individual: (1) feeling safe walking day or night; (2) violence is not a problem; (3) neighbourhood is safe with regard to crimes	CBCL	Deprivation	No	6.5
Ma et al. (2018)	Sydney, Australia	–	Adulthood	562	C	MC	Individual: (1) high crime rate; (2) crime rate makes it unsafe to go on walks during the day; (3) the crime rate makes it unsafe to go on walks at night	MCS	–	No	6
Pals & Kaplan (2013)	Houston, US	–	Adolescence	1333	L	MC	Individual: (1) sexual assaults or rapes; (2) burglaries and thefts; (3) assaults and muggings; (4) organized crime; (5) racial groups not getting along with each other; (6) gangs	Symptoms of anxiety, depressive affect and self-derogation	Economic problems	No	7
Putrik et al. (2015)	Maastricht, The Netherlands	–	Adulthood	9879	C	PC	Individual/Aggregated (four-digit postal code): (1) bike thefts; (2) thefts from the car; (3) damage to car or thefts from outside the car; (4) car thefts; (5) burglaries	K10	–	No	8
Secretti et al. (2019)	6 state capitals in Brazil	Brazilian Longitudinal Study of Adult Health	Adulthood	10,392	C	MC	Individual: (1) feeling safe walking day or night; (2) violence is a problem; (3) neighbourhood is safe with regard to crimes	CIS-R	–	No	7

Abbreviations: BDI, Beck Depression Inventory; C, cross-sectional; CAARMS, Comprehensive Assessment of At-Risk Mental States; CASH, Comprehensive Assessment of Symptoms and History; CBCL, Child Behavior Checklist; CC, case-control; CESD, Center for Epidemiological Studies Depression; CID, Children's Depression Inventory; CIDI (-SF), Composite International Diagnostic Interview (Short Form), CIS-R, Clinical Interview Schedule-Revised; DISC, Diagnostic Interview Schedule for Children; DSM, Diagnostic and Statistical Manual of Mental Disorders; GDS, Geriatric Depression Scale; GHQ, General Health Questionnaire; HADS-D, Hospital Anxiety and Depression Scale–Depression; ICD, International Classification of Diseases; K, Kessler Psychological Distress Scale; L, longitudinal; MC, mixed crime; MCS, Mental Component Summary of SF36; PC, property crime; PCL, Post-Traumatic Stress Disorder Checklist; PDSQ-GAD, Psychiatric Diagnostic Screening Questionnaire subscale for Generalized Anxiety Disorder; PHQ, Patient Health Questionnaire; PQ-BC, Prodromal

Questionnaire-Brief Child Version; PTSD, post-traumatic stress disorder; RQC, Reporting-Questionnaire for Children; SCAN, Schedules for Clinical Assessment in Neuropsychiatry; SCARED, Screen for Child Anxiety Related Emotional Disorders; SDQ, Strengths and Difficulties Questionnaire; STAI, State-Trait Anxiety Inventory; TRF, Teacher's Report Form; VC, violent crime; YSR, Youth Self-Report.

[a] Quality scores were assigned to extracted estimates. For studies with multiple estimates, overall quality scores were reported as averages.

[b] For studies utilising aggregated reports, area of aggregation are provided.

Table 2
Descriptive statistics on study estimates.

	Anxiety (k = 8)	Depression (k = 50)	Psychosis (k = 8)	Psychological distress (k = 37)
Percentage female	53.2%	55.7%	49.5%	52.7%
Average age	35.5	39.9	24.2	29.3
Age groups				
Adulthood, 19+ years	5 (62.5%)	24 (48.0%)	3 (37.5%)	19 (51.4%)
Childhood, 7–12 years	–	4 (8.0%)	2 (25.0%)	10 (27.0%)
Adolescence, 13–18 years	2 (25.0%)	8 (16.0%)	1 (12.5%)	5 (13.5%)
Young adulthood, 19–35 years	–	1 (2.0%)	2 (25.0%)	–
Middle adulthood, 36–60 years	1 (12.5%)	1 (2.0%)	–	1 (2.7%)
Late adulthood, 61+ years	–	12 (24.0%)	–	2 (5.4%)
Population				
Non-disadvantaged	5 (62.5%)	38 (76.0%)	8 (100.0%)	28 (75.7%)
Disadvantaged	3 (37.5%)	12 (24.0%)	–	9 (24.3%)
Area of crime exposure per 1000 people (median)	1.7	4.1	2.1	4.0
Crime measurement				
Objective	5 (62.5%)	23 (46.0%)	6 (75.0%)	27 (73.0%)
Perceived, aggregated	–	8 (16.0%)	1 (12.5%)	3 (8.1%)
Perceived, individual	3 (37.5%)	19 (38.0%)	1 (12.5%)	7 (18.9%)
Crime type				
Mixed	4 (50.0%)	28 (56.0%)	8 (100.0%)	19 (51.4%)
Property	1 (12.5%)	3 (6.0%)	–	7 (18.9%)
Violent	3 (37.5%)	19 (38.0%)	–	11 (29.7%)
Study design				
Cross-sectional	7 (87.5%)	34 (68.0%)	2 (25.0%)	19 (51.4%)
Longitudinal	1 (12.5%)	16 (32.0%)	2 (25.0%)	18 (48.6%)
Case-control	–	–	4 (50.0%)	–
Outcome criteria				
Broad	5 (62.5%)	41 (82.0%)	5 (62.5%)	33 (89.2%)
Narrow	3 (37.5%)	9 (18.0%)	3 (37.5%)	4 (10.8%)
Adjustment for:				
- crime exposure	1 (12.5%)	2 (4.0%)	–	11 (29.7%)
- area deprivation	1 (12.5%)	10 (20.0%)	5 (62.5%)	19 (51.4%)
- area social processes	2 (25.0%)	13 (26.0%)	2 (25.0%)	8 (21.6%)

public health challenges such as the effect of second-hand smoking on cancer (Kim et al., 2018). Considering the large populations living in high crime areas (e.g. top quartile (Chaix et al., 2006; Newbury et al., 2017; Ramey and Harrington, 2019) or tertile (Astell-Burt et al., 2015; Baranyi et al., 2020a; Benjet et al., 2019; Polling et al., 2014; Secretti et al., 2019; Villarreal and Yu, 2017) of the respective sample), at the population-level these present a significant challenge to global mental health. Our results indicated that the impact of neighbourhood-level crime may vary between age groups, with stronger effects among younger (aged 19–35) and older (aged 61<) adults. However, these results were based on one publication for each age group (Astell-Burt et al., 2015; Teychenne et al., 2012), limiting the robustness of this interpretation. It is plausible that living in high-crime neighbourhoods affects mental health differently across the life course (Baranyi et al., 2020a), but future research should examine differential vulnerability to local crime.

Table 3
Pooled neighbourhood crime effects.

	R	95% CI		p-value	Heterogeneity	
		lower	upper		Cochran's Q	p-value
Anxiety (k = 8)	0.05	0.01	0.10	<0.05	19.00	<0.01
Depression (k = 50)	0.04	0.03	0.06	<0.001	225.17	<0.001
Psychosis (k = 8)	0.04	0.01	0.07	<0.05	18.45	<0.01
Psychological distress (k = 37)	0.04	0.02	0.06	<0.001	155.03	<0.001

Studies often implied causal pathways leading from neighbourhood crime exposure to mental ill health. First, living in a high crime area exposes residents to increased social stress linked to mental health through biological mechanisms by disrupting the hypothalamic-pituitary-adrenal axis regulating the stress response (Do et al., 2011), or by causing systematic inflammation in the body (Nazmi et al., 2010). Also, maternal exposure to neighbourhood crime during pregnancy and the first years after birth can affect offspring's cognitive and emotional development leading to higher risk of mental health problems (Ramey and Harrington, 2019). Crime-related maternal stress has been linked to adverse birth outcomes (Clemens and Dibben, 2017), and less positive parenting styles are more common in violent areas (Cuartas and Leventhal, 2020; Cuellar et al., 2015). Second, local crime can influence mental health through resources used to cope with stressors. In high crime areas, avoidance behaviour and thus lower physical activity is more common (Yu and Lippert, 2016), and so are maladaptive coping strategies (e.g. smoking, substance misuse) (Fleischer et al., 2015; Lorenc et al., 2012). In line with this hypothesis, one included study in our review found that the association between neighbourhood violence and depression was partly mediated by low physical activity in high crime areas (Tamura et al., 2020). In addition to unhealthy behaviour, health-promoting community resources are limited in unsafe areas (Ramey and Harrington, 2019), and people experience loneliness more often, affecting their wellbeing (Domènech-Abella et al., 2020). Finally, neighbourhood crime may modify the effect of well-established individual-level risk factors on mental health (Baranyi et al., 2019) or interact with other contextual determinants (e.g. green space) (Ambrey and Shahni, 2017; Lorenc et al., 2012).

Although causation provides a plausible explanation given the overall literature presented in this systematic review (i.e. the link was present also in higher quality longitudinal investigations), this review is based on observational studies and it is not possible to rule out reverse causation or residual confounding. Health-selective migration into

Table 4
Pooled neighbourhood crime effects by study design and crime measurement.

	Depression (k = 50)				Psychological distress (k = 37)			
	R	95% CI		p-value	r	95% CI		p-value
		lower	upper			lower	upper	
Study design								
Cross-sectional	0.05	0.03	0.06	<0.001	0.04	0.02	0.07	<0.01
Longitudinal	0.03	0.01	0.05	<0.05	0.04	0.01	0.06	<0.05
Crime measurement								
Objective	0.02	0.01	0.04	<0.01	0.03	0.01	0.05	<0.05
Perceived, aggregated	0.05	0.03	0.08	<0.001	0.06	0.00	0.11	<0.05
Perceived, individual	0.08	0.06	0.10	<0.001	0.07	0.03	0.10	<0.001

Table 5
Univariate and multivariate mixed-effects models.

	Depression (k = 50)				Psychological distress (k = 37)			
	B	95% CI		p-value	B	95% CI		p-value
		lower	upper			lower	upper	
Univariate Meta-Regression								
Percentage female (in 10)	0.001	−0.005	0.008	0.674	0.009	−0.000	0.019	0.055
Average age (in 10 years)	−0.000	−0.009	0.008	0.923	0.001	−0.000	0.002	0.194
Age groups								
Adulthood	ref				ref			
Childhood	0.035	−0.039	0.108	0.348	−0.015	−0.054	0.025	0.458
Adolescence	0.013	−0.029	0.055	0.538	0.024	−0.027	0.074	0.350
Young adulthood	**0.123**	**0.057**	**0.188**	**<0.001**	–			
Middle adulthood	0.011	−0.066	0.088	0.773	0.002	−0.104	0.107	0.976
Late adulthood	0.015	−0.013	0.044	0.276	**0.118**	**0.036**	**0.201**	**0.006**
Population								
Non-disadvantaged	ref				ref			
Disadvantaged	0.020	−0.013	0.052	0.225	−0.018	−0.065	0.028	0.427
Area of crime exposure per 1000 people	−0.000	−0.000	0.000	0.587	−0.000	−0.000	0.000	0.881
Crime measurement								
Objective	ref				ref			
Perceived, aggregated	0.027	−0.001	0.056	0.060	0.027	−0.030	0.084	0.349
Perceived, individual	**0.051**	**0.026**	**0.077**	**<0.001**	**0.037**	**−0.000**	**0.075**	**0.050**
Crime type								
Property	ref				ref			
Violent	0.008	−0.038	0.055	0.720	−0.008	−0.055	0.040	0.747
Mixed	0.007	−0.041	0.056	0.765	−0.009	−0.054	0.037	0.704
Study design								
Cross-sectional	ref				ref			
Longitudinal	−0.018	−0.044	0.007	0.160	−0.006	−0.044	0.032	0.767
Outcome criteria								
Broad	ref				ref			
Narrow	−0.007	−0.040	0.027	0.692	0.035	−0.024	0.093	0.236
Adjustment for:								
- crime exposure	0.006	−0.060	0.072	0.861	−0.013	−0.055	0.030	0.552
- area deprivation	**−0.039**	**−0.067**	**−0.011**	**0.008**	**−0.035**	**−0.067**	**−0.004**	**0.031**
- area social processes	0.007	−0.018	0.032	0.598	−0.010	−0.055	0.035	0.651
Quality Score	−0.003	−0.010	0.004	0.359	−0.000	−0.011	0.011	0.937
Multivariate Meta-Regression								
Intercept (r)	**0.031**	**0.012**	**0.050**	**0.002**	**0.028**	**0.000**	**0.056**	**0.049**
Age groups								
Adulthood	ref				ref			
Childhood	0.030	−0.044	0.104	0.412	−0.011	−0.049	0.027	0.556
Adolescence	−0.018	−0.060	0.024	0.398	0.010	−0.037	0.058	0.663
Young adulthood	**0.088**	**0.028**	**0.148**	**0.005**	–			
Middle adulthood	0.011	−0.060	0.082	0.761	0.007	−0.093	0.107	0.886
Late adulthood	0.014	−0.011	0.038	0.279	**0.124**	**0.044**	**0.204**	**0.003**
Crime measurement								
Objective	ref				ref			
Perceived, individual	**0.034**	**0.006**	**0.062**	**0.019**	**0.039**	**0.005**	**0.073**	**0.025**
Perceived, aggregated	0.013	−0.016	0.042	0.366	0.032	−0.019	0.083	0.210
Adjustment for:								
- area deprivation	*−0.024*	*−0.051*	*0.002*	*0.071*	−0.013	−0.046	0.019	0.411

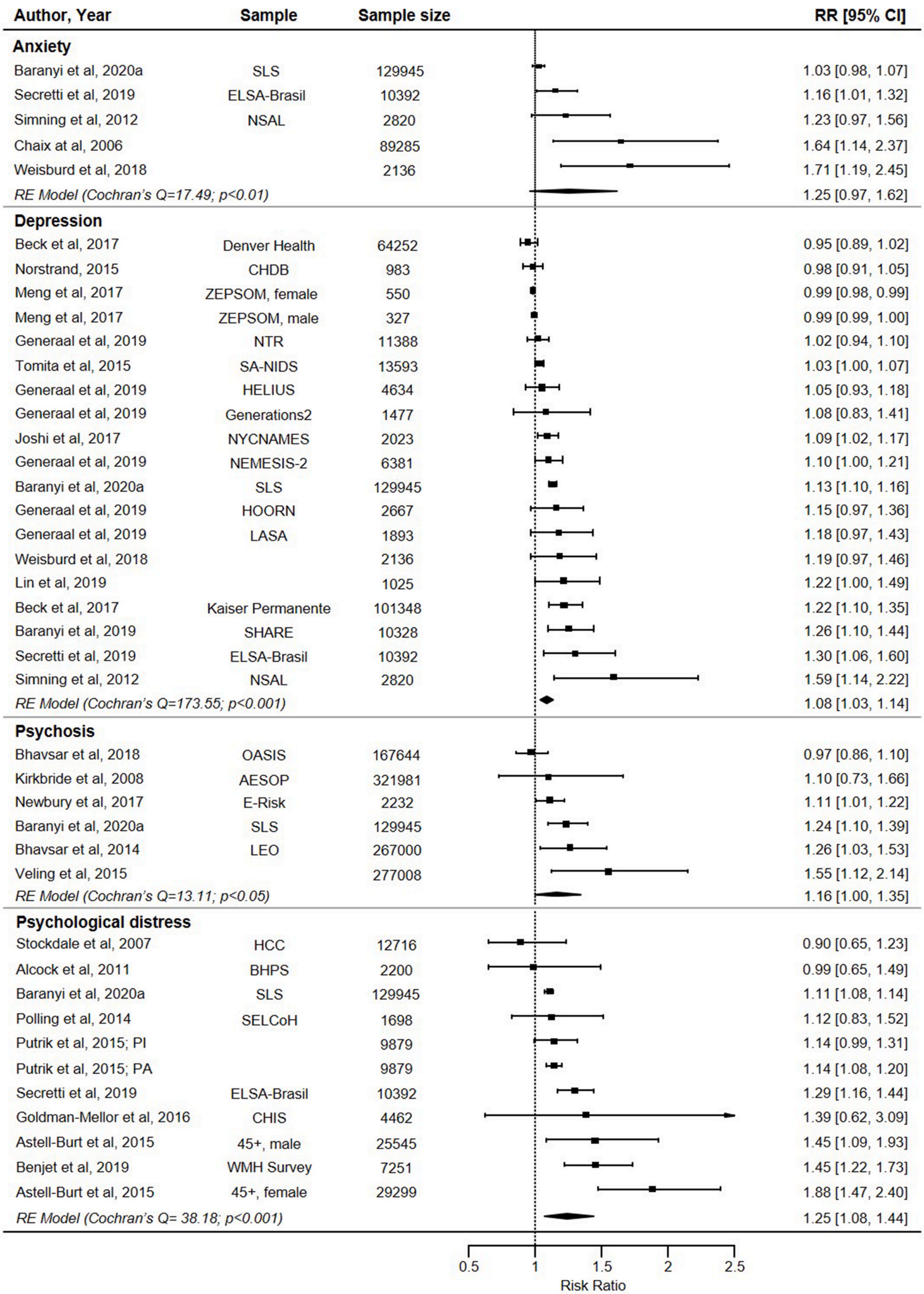

Fig. 2. Three-level random-effects meta-analyses of neighbourhood crime estimates on binary mental health outcomes. Abbreviations: RE, random-effects; PI, perceived crime, individual-level; PA, perceived crime, aggregated.

socially disadvantaged and high-crime areas, as part of a downwards drift of social selection through unemployment and low income, may help to drive these associations, especially among middle-aged individuals with pre-existing mental health conditions (Baranyi et al., 2020b). Also, higher risk of crime victimisation among people with existing mental health problems (Dean et al., 2018) might further complicate the crime-mental health relationships.

Pooled effect sizes were larger if exposure was measured using participants' perceptions of local crime rather than objectively recorded crime incidents. The indirect effect of crime might be mediated through the perception of residents (Lorenc et al., 2012), for example whether they are aware of potential danger and threat in their neighbourhood. This would explain stronger associations for perceived crime as being a more proximal risk factor to mental health. However, studies empirically testing the relationship between perceived and objective crime indicate only a modest correlation (Goldman-Mellor et al., 2016; Wilson-Genderson and Pruchno, 2013) and measurement-specific errors likely lead to overestimation of perceived and underestimation of objective crime effects. First, participant-reported crime and mental health within the same study increases the risk of same source bias (i.e. correlated measurement errors) (Diez Roux, 2007; O'Brien et al., 2019), and reverse causation (i.e. people with mental health conditions perceive their neighbourhood as more dangerous). Second, as crimes and offences are notoriously underreported, especially in more disadvantaged neighbourhoods, objectively measured incidents originating from administrative data (e.g. police reports) do not capture the 'real' levels of crime (Scottish Government, 2019). Third, crime records are usually aggregated within researcher-defined geographic areas around participants' residential address or within arbitrary administrative units (e.g. census tract), which are unlikely to coincide with people's self-defined neighbourhood and therefore their real exposure based on daily activities (Diez Roux, 2007). Despite criminological research implying that crime is concentrated in a few hot spots (law of crime concentration) (Jones and Pridemore, 2018; Weisburd et al., 2018) providing an adequate spatial specificity for assessing crime effects (Weisburd et al., 2018), the geographic scale of areas within this review varied enormously and often without clear theorisation or interpretation of geographic scale. Only very few studies considered systematically testing different scales of crime exposure (Chaix et al., 2006; Cuartas and Roy, 2019; Weisburd et al., 2018), and these generally found stronger associations at smaller scales.

Finally, studies with objectively measured crime were, in the majority of cases, adjusted for other area-level characteristics, which likely lead to overadjustments, and in more extreme cases – if area-level characteristics are highly correlated (i.e. multicollinearity) – to biased estimates and inflated standard errors. Univariate meta-regression found weaker crime-mental health associations in studies controlling for area-level deprivation. Neighbourhood socioeconomic disadvantage is associated with depression as shown by a meta-analysis of longitudinal studies with short-term follow up (Richardson et al., 2015). Area deprivation presents a cluster of causal mechanism likely to co-occur in places, including poverty and disadvantage at individual-level. Neighbourhood crime is one of the few plausible mechanisms operating at area-level, which explains higher risk of mental health problems in disadvantaged communities (Baranyi et al., 2020a; Joshi et al., 2017). Therefore, adjusting for area-level deprivation in the models is likely to underestimate the impact of neighbourhood crime.

4.1. Strengths and limitations

This systematic review applied rigorous selection criteria (for example, we separated perceived crime from several related concepts such as neighbourhood disorder and feeling of safety), included only confounder-adjusted estimates as a response to earlier critiques (O'Brien et al., 2019), explored heterogeneity across methodological and sample characteristics, and tested the robustness of findings in a wide range of sensitivity analyses. Findings on the association between neighbourhood crime, depression and psychological distress were present regardless of study design and type of crime measurement.

However, it has limitations. First, studies had varying quality and limited geographic coverage (83% of studies were from high-income countries). Second, data on anxiety and psychosis were scarce, and for the latter the majority of included publications were either relying on data from population-based case-control studies, or the outcomes were more common presentations such as psychotic-like experiences. Findings on these outcomes require cautions interpretation. Third, crime operationalisation, study design and statistical approaches varied substantially across studies; therefore, effect estimate transformation inherently led to less precise findings, especially for continuous outcomes. Last, as only a handful of studied adjusted for direct exposure to crime in the neighbourhood, we were unable to separate indirect crime effects from the impact of direct crime exposure (Cuartas and Leventhal, 2020; Cuartas and Roy, 2019); therefore it is likely both contributed to our findings.

4.2. Future research

Future research should strengthen the knowledge base by applying more robust research designs. While it is challenging to apply randomised experimental approaches in neighbourhood research, utilising natural- or quasi-experimental design merits further attention (Diez Roux, 2007). Crime levels are not constant and research can take usefully advantage of fluctuating changes across neighbourhoods over time (Astell-Burt et al., 2015; Baranyi et al., 2020b). Exploring the impact of wider social and economic policies on crime levels, as well as practices in law enforcement and policing aiming to prevent crime, are important venues for future research. To address these time-sensitive research questions, administrative data on mental health are particularly useful.

Cohort studies with repeated measurements of neighbourhood-level crime and individual-level mental health could help to disentangle the complex causal mechanisms. The application of life course approaches is particularly promising (Pearce et al., 2018). Identifying sensitive developmental periods where living in high crime areas may have long-term impacts on behaviour and mental health, or potential accumulation of crime effects over the life course, are important research questions. Life course investigations have also the potential to overcome challenges related to health selective migration. Finally, identifying vulnerable sociodemographic groups over the lifespan and exploring crime effects between different mental disorders may help to better target policies and interventions.

The findings from this review also emphasise the importance of developing and applying theoretically appropriate methods for capturing neighbourhood-level crime, and ensuring the geographic scale of these measures is consistent with the hypothesised pathways connecting local crime and mental health. For example, research examining the impact of urban crime on health may consider applying microgeographic units of exposure in order to capture the localised experiences and spatial concentration of crime (Jones and Pridemore, 2018; Weisburd et al., 2018). On the other hand, capturing the effect of organised crime by drug trafficking organisations arguably requires developing measures for wider geographical units (e.g. cities, regions) in order to recognise the more spatially dispersed impacts of these actions (Villarreal and Yu, 2017). Importantly, applying static measures of neighbourhood crime based on residential addresses is unlikely to fully capture crime exposure and experiences of crime; novel methods modelling participants' activity space with GPS tracking is a promising avenue for future research (Kwan et al., 2019).

Finally, there is also a need for new research that leads to a better understanding of the causal pathways connecting neighbourhood crime and individual-level mental health. Galster's framework of neighbourhood effects – particularly the four broad rubrics of causal mechanisms – is useful here (Galster, 2012). Applying this framework to the neighbourhood crime and mental health literature emphasises that whilst there are a number of studies investigating environmental (i.e. natural and human-made physical attributes including neighbourhood infrastructure, litter and toxic substances) and geographical mechanisms (i.e. emphasising macro-level political and economic factors that limit the local tax base or restrict local employment opportunities), few studies have grappled with social interactive mechanisms (i.e. social processes such as the collective norms or networks and cohesion between residents) or institutional (i.e. processes external to the neighbourhood resulting for example in place-based stigmatisation or unequal public and private investment) mechanisms.

5. Conclusions

Crime in residential areas is a significant public health, social, economic and legal concern, requiring systems-based approaches in policy and intervention and cooperation between professionals tasked with crime and (mental) health services. Allocating universal or targeted mental health preventions in the vicinity of high crime areas present opportunities to reduce the incidence of mental disorders, and can be particularly useful in early ages where skills and coping strategies can be acquired (e.g. in school context) (Werner-Seidler et al., 2017). Providing access to mental health services and treatments, including early detection and specialised programmes for severe mental illnesses (Nossel et al., 2018), would not only help to lower the mental health burden in disadvantaged communities but also tackle individual-level determinants of ill health (e.g. unemployment). However, healthcare professionals should be mindful about the comparably worse mental health treatment outcomes in high crime neighbourhoods, requiring an average higher number of treatment sessions and new approaches augmenting psychological interventions with empowerment and skill development training (Finegan et al., 2020). As local practitioners alone might be relatively powerless tackling the impact of local crime and violence, healthcare planners and policy makers should be aware of health needs related to area crime. Finally, hot spot policing (Weisburd et al., 2018), complex neighbourhood-based interventions targeting both physical (e.g. reducing alcohol availability, area rehabilitation, greening vacant parcels) (Kondo et al., 2018) and social (e.g. increasing social cohesion, building community facilities) (White et al., 2017) determinants of crime, as well as macro-level interventions (e.g. reducing harms related to poverty) are best able to address crime and violence (Jones and Pridemore, 2018; Lorenc et al., 2012) and may have benefits for population mental health.

Author contributors

GB, CD, TCR, and JP conceived, planned, and oversaw the study. GB and MHDM searched the literature, applied inclusion and exclusion criteria, and conducted quality assessment; disagreements between reviewers were resolved by consensus with JP GB extracted data, MHDM cross-checked them. GB developed the methodology and conducted the statistical analyses. GB drafted the manuscript; all authors reviewed, commented on, and approved it.

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Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2021.114106.

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